August 4, 2025

Lilah Shema-Zlatokrilov, ADV.CPA (ISR)

The Hebrew University of Jerusalem, School of Business Administration

& Research Department, the Bank of Israel

Dear Committee Members,

Subject: Application for NBER PhD Student Workshop on Climate Finance

I am writing to apply for the NBER PhD Student Workshop on Climate Finance to be held on October 9, 2025. I am a PhD candidate in Finance at the School of Business Administration, The Hebrew University of Jerusalem, working under the supervision of Prof. Dan Galai and Prof. Zvi Wiener, while currently serving as a researcher in the Research Department at the Bank of Israel.

My interest in climate finance is rooted in my background in regulatory and development banking, where I observed how financial institutions' disclosure strategies can either promote or hinder true environmental and social progress.

My PhD research plan comprises three interconnected papers examining the ground conditions of greenwashing risk in the banking sector: **Paper 1: "Spotting 'Washing': Can Financial Experts Detect 'Say-Do Gap' in Banking Reports"** (Co-authors A. Hurwitz and S. Nolte); Employing an innovative experimental design that combines eye-tracking technology with a questionnaire for behavioral analysis, we examine 128 financial professionals as they evaluate banking communications containing embedded contradictions (ambiguities) related to the strategic implementation of ESG. Digital innovation claims serve as a crucial control domain. Our findings reveal that the identification of potential greenwashing operates through specialized cognitive pathways distinct from general analytical capabilities. Attention to ESG contradictions significantly predicts a higher level of identification of potential greenwashing, independent of personality characteristics. Contextual framing moderates both detection and investment outcomes, with ESG emphasis amplifying the negative impact on investment recommendations. **Paper 2: "Cognitive Attention and Text Sentiment in ESG and Innovation Disclosures"** (Co- author J. Benchimol)**;** Building on the first paper's data, we examine the relationship between attention patterns and sentiment analysis. **Paper 3: Do Banks Strategically Use ESG Language?** The third paper will close the theme by Analyzing how ESG narratives in managements' letters change following adverse reputation events, investigating whether banks systematically increase ambiguous ESG language as a defensive strategy.

Throughout my career, I have developed a robust knowledge and expertise in financial regulation and risk management, which I implement as an early career researcher. Using Tobii eye-tracking technology that I have specialized, we capture precisely how experts allocate attention when encountering disclaimers and contradictory statements in managements' statements. This methodology reveals whether experts recognize ambiguities as warning signals—critical for climate finance integrity and financial stability supervision globally. The documented reduction in investment recommendations when greenwashing is detected demonstrates direct market impact with implications for international capital flows toward genuine climate solutions. Our findings have significant implications for future research and policy

developments in climate finance. Methodologically, the integration of eye-tracking technology with behavioral finance opens new avenues for objective measurement of attention in financial decision-making.

This workshop offers an invaluable opportunity to engage with leading international researchers who are shaping the future of climate finance. I look forward to receiving critical feedback on my experimental methodology and exploring how attention-based greenwashing detection mechanisms can be adapted to various regulatory environments and integrated with other research methods. The networking opportunities will be crucial for developing collaborations that extend my research beyond its current framework. Additionally, the workshop will provide a unique platform to refine my research and contribute to global policy discussions on climate finance integrity. The insights gained will be essential for both my academic growth and my work at the Bank of Israel.

Details

- **Expected PhD completion**: December 2026
- **Faculty References**: Prof. Dan Galai (dan.galai@mail.huji.ac.il) and Prof. Zvi Wiener (zvi.wiener@mail.huji.ac.il)
- **Paper for Workshop**: "Spotting 'Washing': Can Financial Experts Detect 'Say-Do Gap' in Banking Reports"

Thank you for considering my application.

Sincerely,

Lilah Shema-Zlatokrilov

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Education:

- PhD student in Finance, Hebrew University of Jerusalem (2022–Present). ESG, Banking sector, Experimental finance (experimental surveys and Tobii lab experiments' design and execution).
- Bank's Innovation Index – Thesis paper, Research in Finance, Hebrew University of Jerusalem (March 2021); Selected advanced finance courses, Pre-PhD program, Hebrew University of Jerusalem (2017–2020)
- B.A. in Accounting, Hebrew University of Jerusalem (2004)
- M.A. in Economics, Hebrew University of Jerusalem (1999)
- B.A. in Economics and Law, Hebrew University of Jerusalem (1997)

Licenses and training:

- Advocate License, Israel No. 23925
- CPA License, Israel No. 500104694
- MoneyVal Training, Council of Europe – Prohibition of Money Laundering and Terrorist Financing (July 2010)

Working Papers - Published:

- Berzani, Yehonatan & Shema - Zlatokrilov, Lilah. (2025). Exploring SMEs' Insolvency: A Nonfinancial Statement Model Using "Red Flag" and Macroeconomic Indicators. SSRN Electronic Journal. 10.2139/ssrn.5241813.
- Plato-Shinar, R., Maman, L., Shema Zlatokrilov, L., & Yaacobi, N. (2025). The Willingness of the Public to Adopt a Digital Shekel: Research Conclusions Report. Bank of Israel. Available at SSRN.
- Shema- Zlatokrilov, Lilah. Do words create reality? The development of fintech-banking as seen in financial reports (October 21, 2021). Available at SSRN.

Working Papers – In Preparation:

- Hurwitz, A., Nolte, S., & Shema-Zlatokrilov, L. (2025). Spotting "Washing": Can Financial Experts Detect "Say-Do Gap" in Banking Reports?
- Lilah Shema – Zlatokrilov (2025). Pay Now, Regret Later? The Impact of Payment Risk Prompts on Consumer Behavior and Post-Purchase Satisfaction.

Work History:

- Bank of Israel Research Department – Researcher and Senior specialist (Financial Department – Macro Prudential unit) (July 2019–Present): Research main topics ESG, Initiating the research on public adoption of local CBDC, Behavioral experimental finance, Innovation, Banking Sector, Policy notes on Financial Stability & Financial Regulations, ISR Securitization new law and database.
- Banking Supervision Department, Bank of Israel (November 2014–July 2019). Head of business continuity in the banking system - Banking Supervision Department, Bank of Israel; crisis management team specialist; Methodology of Handling Banks in Difficulties and Bank Failure.
- Inter-American Bank for Development of Latin America and the Caribbean (July 2011–July 2014). Senior Advisor to the Board of Directors: Consultant and senior advisor; Board member in international economic organizations.
- Banking Supervision Department, Bank of Israel (August 2008–July 2011) Head of Anti-Money Laundering and Counter-Terrorist Financing: member of the Sanctions Committee.
- Banking Supervision Department, Bank of Israel (September 2001–August 2008). Basel 2 Implementation Team member. Examiner specialized in credit risk and customer protection.
- Attorney and Intern, Economic Department of the Attorney's Office (1995–September 2007): Economic crimes; team member in major Israeli cases (La National Insurance Company, Gregory Lerner.

Academic Activity:

- Academic Assistant, Crowdfunding and Alternative Markets Course, Hebrew University of Jerusalem (2021–2024)

Volunteering:

- Head of the research committee at the Israeli Coaching Chamber – responsible for establishing a new research division (2024- present).
- Board Member and Content & Learning Team Member, Israeli Chapter of the International Coaching Federation (ICF) (2023–Present).
- Active Executive and Life Coach & Mindfulness Guide – Integrated Coach specialized in CBT and Positive Psychology Practices, License: ICF – PCC (2021 – Present).
- Volunteer at the Mental Assistance Aid Line (Eran Israel) (2023–Present).
- Assistance to the Executive Committee, Natan International Humanitarian Aid (2017).

Spotting "Washing": Can Financial Experts Detect "Say-Do Gap" in Banking Reports

Abigail Hurwitz[1], Sven Nolte[2], Lilah Shema – Zlatokrilov[3]

Abstract

We investigate how financial experts detect potential greenwashing in corporate ESG communications through attention mechanisms and cognitive processing pathways. Employing an innovative experimental design that combines eye-tracking technology with a questionnaire for behavioral analysis, we examine 128 financial professionals as they evaluate banking communications containing embedded ambiguities related to the strategic implementation of ESG. Digital innovation claims serve as a crucial control domain. Our findings reveal that the identification of potential greenwashing operates through specialized cognitive pathways distinct from general analytical capabilities. Attention to ESG contradictions significantly predicts a higher level of identification of potential greenwashing, independent of personality characteristics. Contextual framing moderates both detection and investment outcomes, with ESG emphasis amplifying the negative impact on investment recommendations. We also uncover a "skepticism paradox," and that understanding climate risk enhances the identification of greenwashing. These domain-specific effects, which are markedly weaker for digital washing, confirm specialized cognitive processing for ESG evaluation, advancing expert judgment theory, and providing actionable insights.

Keywords: Greenwashing, Say-do gap, Eye-tracking, Expert judgment, attention, ESG communications, Sustainable finance, Investment decisions

JEL Classification : G11, G14, G41, M14, Q56

1. Introduction

The proliferation of environmental, social, and governance (ESG) reporting has created unprecedented challenges for financial market participants seeking to distinguish genuine sustainability commitments from greenwashing—the practice of conveying false impressions about environmental practices. This "say-do gap" between stated commitments and actual implementation poses a significant threat to market efficiency, as systematic information asymmetries hinder optimal capital allocation toward genuinely sustainable enterprises. Recent evidence highlights the magnitude of the issue. While 67% of EU banks report involvement in green financing activities, only 23% substantiate these claims with quantitative targets or performance indicators (European Banking Authority[4], 2022, p. 47). Furthermore, the identification of greenwashing leads to an average 6.2% decrease in credit ratings (Alizadeh et al., 2024).

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[4] https://www.eba.europa.eu/sites/default/files/document_library/Publications/Reports/2023/1055934/EBA%20progress%20report%20on%20greewnwashing.pdf

Despite extensive regulatory attention and growing academic literature on greenwashing practices, fundamental questions remain about how financial experts detect these deceptive communications. Existing research has documented the prevalence and market consequences of greenwashing but has not examined the cognitive mechanisms underlying expert detection capabilities. Three critical knowledge gaps persist. First, the role of attention in processing complex ESG communications remains unexplored, despite evidence that limited attention can create systematic biases in financial evaluation (Hirshleifer & Teoh, 2003). Second, the relationship between individual characteristics and the probability of detecting greenwashing lacks systematic investigation, with emerging evidence suggesting counterintuitive patterns where certain types of expertise may paradoxically impair detection capabilities. Third, the decision process linking detection capabilities to investment choices remains unclear, limiting our understanding of how expert judgment translates into capital allocation decisions.

The primary purpose of this study is to identify the ground conditions for greenwashing risk in the banking sector by understanding the cognitive mechanisms that lead to the identification of greenwashing. Our research aims to uncover the cognitive processes that lead to the identification of greenwashing, with a focus on the role of attentional pathways in this process. We examine whether domain-specific cognitive pathways influence the detection of greenwashing, comparing detection mechanisms across the environmental (greenwashing) and innovation transformation (digital washing) domains.

We investigate the role of attention in detecting potential greenwashing, examining whether attention allocation (“external attention”) operates independently of evaluation processes (“internal attention”). Ultimately, we examine how the identification of potential greenwashing leads to revisions that correlate with investment recommendations, and how personal characteristics and traits influence this process.

We address these questions through an innovative experimental methodology and design that combines external and internal manipulations, measured by eye-tracking technology, and followed by a detailed questionnaire that includes subjective evaluations as well as questions on habits, Knowledge, and beliefs in the context of ESG and digital banking.

We examine 128 financial professionals evaluating banking demo communications containing embedded ESG contradictions, using digital innovation claims as a control domain to isolate ESG-specific detection mechanisms. This approach enables objective measurement of attention allocation alongside subjective evaluation processes. Our experimental stimuli are based on authentic banking reports, featuring carefully designed contradictions between stated ESG commitments and reported operational metrics, thereby ensuring ecological validity while maintaining experimental control.

Our research yields three primary contributions to the literature on sustainable finance. First, we demonstrate that greenwashing detection operates through attention pathways, as evidenced by systematic differences between ESG and digital domains in detection mechanisms. Second, we establish a correlation between detection capabilities and investment recommendations, providing evidence for the market-level significance of expert judgment quality in sustainable finance and showing that contextual framing significantly moderates both detection and investment processes. Third, we identify counterintuitive patterns in expert judgment, including a "skepticism paradox" where greater media awareness paradoxically reduces sensitivity to greenwashing. We also demonstrate that attention operates independently of personality characteristics, suggesting separate cognitive mechanisms for attention allocation and critical evaluation. These findings advance understanding of expert judgment while providing actionable insights for financial education, regulatory policy, and corporate

communication strategies. For financial education, our results suggest that training programs should prioritize skills in processing and domain-specific knowledge over general analytical capabilities. For regulatory policy, the findings underscore the crucial importance of information presentation standards and the necessity for ESG-specific disclosure frameworks. For market efficiency, the results demonstrate that the quality of expert judgment directly affects capital allocation toward genuinely sustainable enterprises, with implications for the development of decision-support tools that enhance detection capabilities.

The remainder of this paper proceeds as follows: Section 2 reviews literature on greenwashing detection and expert judgment, developing our theoretical framework and hypotheses. Section 3 describes our experimental methodology, including eye-tracking procedures and the development of stimuli. Section 4 presents comprehensive results addressing each research question. Section 5 discusses theoretical implications, practical applications, and limitations.

2. Literature Review and Theoretical Framework

2.1 Literature Review

Greenwashing poses a significant challenge to market efficiency in sustainable finance, creating information asymmetries that hinder optimal capital allocation toward genuinely sustainable enterprises (De Freitas Netto et al., 2020). The financial consequences of greenwashing are substantial and well-documented. Alizadeh et al. (2024) found that the identification of greenwashing leads to an average 6.2% decrease in credit ratings, while ESG-related controversies generate measurable firm value destruction through adverse market reactions (Aouadi & Marsat, 2018). Reputational crises directly correlate with declining bank valuations (Gatzert et al., 2015). Key drivers of reputational risk include environmental governance failures, operational inefficiencies, and unethical management practices (Michaelowa et al., 2020; Zaby and Pohl, 2019).

ESG ratings have a significant impact on investor preferences, necessitating the optimization of portfolios (Pedersen et al., 2021). Ultimately, real-world cases were documented, including those of Commonwealth Bank Australia, which experienced a 13% stock decline after ESG document disclosure, and DWS/Deutsche Bank, which saw a 7% drop following an investigation into false ESG claims.

Aggarwal and Kadyan (2011) examined greenwashing practices across various sectors and found them to be prevalent, regardless of overall CSR scores. They concluded that stricter regulations and guidelines are necessary to curb greenwashing practices, and companies should strive for genuine sustainability and transparent communication to establish trust among stakeholders. In the specific context of "washing" detection, Lyon and Montgomery (2015) and Delmas and Burbano (2011) investigated how companies mislead stakeholders about their environmental practices, while Furlow (2009) demonstrated that such deception can significantly damage consumer trust.

The "say-do gap"—the discrepancy between what companies claim and what they do—poses significant reputational risks, mainly when stakeholders are motivated by ESG concerns but corporate leadership is not. Banking institutions face particularly acute pressures due to what Ofir and Elmakiess (2023) characterize as the "eco-agency problem," a fundamental conflict between short-term profitability pressures and long-term sustainability goals that creates systematic incentives for unethical behavior. The critical question is whether stakeholders and rating agencies can accurately distinguish between genuine

and non-genuine ESG commitments, especially given the increasing complexity of corporate disclosures and the subjective nature of sustainability evaluations. The detection of greenwashing requires sophisticated information processing that integrates environmental knowledge, financial analysis skills, and critical evaluation capabilities. Dual-process theory (Evans, 2008) provides a framework for understanding how experts process ESG communications: System 1 processes generate rapid impressions based on surface-level ESG cues, while System 2 processes enable deliberate analysis of consistency between stated commitments and reported metrics. For example, Seifert et al. (2024) demonstrated that higher sustainable finance literacy leads to more sustainable investments and fewer greenwashed investments, highlighting the importance of financial education in combating greenwashing.

Attention theory offers crucial insights into how experts allocate cognitive resources when evaluating ESG communications. Hirshleifer & Teoh (2003) demonstrate that limited attention creates systematic biases in financial evaluation, with implications for detecting subtle inconsistencies in complex ESG disclosures. Recent extensions by Cordes et al. (2023) show that attentional patterns actively shape judgment under cognitive constraints, suggesting that experts may overlook ESG contradictions when overwhelmed by information complexity.

Framing effects fundamentally alter how experts interpret ESG information. Kahneman & Tversky's (1979) foundational work on prospect theory demonstrates that initial presentation systematically shapes responses to subsequent information. In ESG contexts, Levin et al. (1998) show that optimistic ESG framing increases responsible investment intentions among professionals, while contextual emphasis on environmental benefits can overshadow contradictory operational evidence.

Research reveals complex individual differences that shape greenwashing detection capabilities, often in counterintuitive ways. A "skepticism paradox" arises in ESG contexts, where heightened awareness of regulatory and media dynamics may paradoxically reduce sensitivity to specific instances of greenwashing. This occurs because experts who are highly aware of general ESG communication strategies may develop generalized skepticism that reduces attention to contradictions.

Conversely, climate-related economic risk awareness significantly enhances the detection of greenwashing. Krueger et al. (2020) found that institutional investors with heightened climate risk awareness improved their accuracy in identifying greenwashing by 32% compared to control groups. This enhancement operates through economic rather than environmental frameworks—experts focus on the financial materiality of climate risks rather than abstract environmental concerns, enabling systematic evaluation of consistency between sustainability claims and economic realities.

Systematic gender effects appear in ESG evaluation contexts. Research has revealed apparent gender differences in approaches to analyzing financial information and decision-making processes. For example, female investors tend to be more cautious, conduct more thorough due diligence, and exhibit lower levels of overconfidence compared to their male counterparts, which often leads to better investment outcomes and reduced unnecessary risks (Barber & Odean, 2001). Comprehensive reviews further indicate that women are more likely to evaluate information and cross-check data from multiple sources systematically, while men are more prone to take risks and make quicker decisions (Croson & Gneezy, 2009).

These findings suggest that women may have a relative advantage in due diligence and risk assessment processes, which could also translate into enhanced detection of issues such as greenwashing.To isolate ESG-specific detection mechanisms, we compare greenwashing detection with digital washing

identification. Unlike environmental reporting, which benefits from established frameworks (GRI, SASB, TCFD), digital transformation disclosures remain largely unregulated (Arner et al., 2020). This creates different cognitive processing requirements: ESG evaluation relies on established knowledge of sustainability and regulatory frameworks, while digital evaluation depends more on technological familiarity and innovation assessment skills.

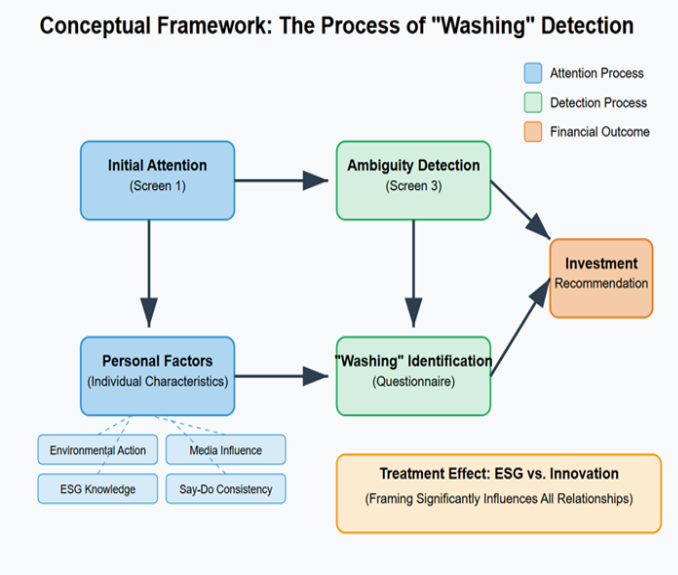
If greenwashing detection operates through specialized cognitive pathways, we should observe ESG-specific effects that do not extend to digital washing. Conversely, if detection capabilities reflect general analytical skills, similar patterns should emerge across both domains. This comparison enables definitive conclusions about the domain specificity of greenwashing detection mechanisms.

Visual attention represents a critical component in cognitive processing models, yet its measurement poses significant methodological challenges. Direct questioning about attention allocation risks influencing the very phenomenon under investigation, creating measurement artifacts that compromise research validity. Eye-tracking technology provides a robust solution to this methodological challenge by capturing participants' gazing behavior as they visually process information, thereby offering objective measures of overt attention (Blair et al., 2009; Duchowski, 2007; Sulflow, Schafer, & Winter, 2019). The theoretical foundation for eye-tracking as an attention measure rests on the eye-mind assumption developed by Just and Carpenter (1980), which posits that visual fixations—periods when gaze rests on specific stimulus elements—correspond directly with attention allocation and cognitive processing intensity. This relationship suggests that areas receiving longer, or more frequent fixations, undergo more elaborate cognitive processing than briefly viewed or ignored content. Empirical validation of this assumption is provided by studies demonstrating positive correlations between fixation patterns and memory performance for fixated elements, which supports the interpretation of eye-tracking parameters as indicators of cognitive elaboration (Loftus, 1972; Wedel & Pieters, 2000).

However, eye-tracking methodology has important limitations that researchers must acknowledge. While technology effectively captures where and how long participants look at specific content, it cannot specify the underlying cognitive processes driving these fixation patterns—whether attention stems from interest, confusion, surprise, or other cognitive states (Vraga et al., 2015). Additionally, eye-tracking measures overt attention cannot capture covert attention shifts that occur without corresponding eye movements. These constraints require researchers to develop explicit theoretical assumptions about the cognitive processes that are likely to direct attention distribution within experimental stimuli, ensuring the appropriate interpretation of eye-tracking data within the broader research framework. In our setting, this was done by a questionnaire that followed the eye-tracking phase.

2.2 Research Questions and Hypotheses Development

Figure 1: Experimental Behavioral Model



Our research integrates these theoretical and practical methodological frameworks to understand the mechanisms of washing identification through a combination of eye-tracking and a questionnaire experiment. We primarily utilize the Framing Effects Theory (Kahneman & Tversky, 1979), Visual Attention Theory (Hirshleifer & Teoh, 2003), Dual-Process Theory (Evans, 2008), and attention theory with cognitive load models that integrate personal traits (Cordes, Nolte, & Schneider, 2023).

Building on this theoretical framework, we develop research questions as an analysis path that systematically examines the cognitive mechanisms underlying a potential greenwashing identification and its correlation with investment recommendations. Thus, our approach traces the complete decision-making pathway from initial information processing to final investment outcomes, using digital washing as a control to isolate ESG-specific effects.

Our experimental framework examines attention and washing detection through two distinct channels that capture different aspects of cognitive processing. The first channel operates through Screen 1, where we manipulate external attention by directing participants to focus systematically on either ESG sustainability features or digital innovation characteristics, creating domain-specific cognitive priming that influences subsequent information processing. The second channel operates through Screen 3, where we measure internal attention patterns as participants naturally read and evaluate corporate disclosure materials, capturing spontaneous attention allocation to contradictory information. Together, these channels enable us to examine how directed attention (external manipulation) and spontaneous attention patterns (internal measurement) influence the detection of contradictions and the identification of washing in investment recommendation decision-making (Figure 1)

We employ digital innovation claims as a control to isolate ESG-specific detection mechanisms from general analytical capabilities. Unlike environmental reporting, which has established frameworks (GRI,

SASB, TCFD), digital transformation disclosures remain largely unregulated, creating opportunities for "digital washing" where 41% of banking AI claims lack verifiable metrics (Shiyyab et al., 2023; Bernini et al., 2023). This comparison enables definitive conclusions about cognitive specificity: if greenwashing identification represents specialized ESG processes, effects should not extend to digital washing; if detection reflects general analytical skills, similar patterns should emerge across both domains.

Research Question 1: (Visual) Attention and Identification Mechanisms

Our first research question addresses the fundamental cognitive process underlying the identification of potential greenwashing. When experts systematically direct attention toward identifying inconsistencies between stated sustainability commitments and actual practices, they develop enhanced pattern recognition capabilities that facilitate potential washing Identification. This attention-detection relationship should be particularly pronounced in ESG contexts, where the complexity and strategic ambiguity of sustainability claims create numerous opportunities for contradictory messaging.

RQ1: How does financial experts' attention to sustainability versus innovation contradictions affect their ability to identify washing in respective disclosures?

H1a: Attention to contradictions positively relates to potential greenwashing identification; H1b: This relationship is stronger in ESG contexts than in digital domains.

Research Question 2: Identification Impact on Investment Recommendation

The second research question examines the translation of potential greenwashing Identification into investment recommendations. Once experts identify potential washing behaviors, this detection should logically influence their investment decisions through risk adjustment mechanisms. The theoretical basis draws from rational decision-making models in finance, where identification of deceptive practices leads to appropriate valuation adjustments. However, the domain-specific nature of this relationship requires careful consideration. Greenwashing Identification may generate stronger negative investment reactions than digital washing detection because sustainability risks increasingly represent material financial risks affecting long-term firm value, regulatory compliance, and market positioning.

RQ2: How does contradiction identification and washing identification impact investment recommendations?

H2a: Washing and contradiction identification negatively impact investment recommendations; H2b: This effect is more pronounced for greenwashing than digital washing. The same hypotheses are also tested for the digital domain.

Research Question 3: Individual Characteristics and Identification Capabilities

The third research question acknowledges that washing detection capabilities may vary systematically across experts, depending on individual characteristics and domain-specific expertise. Experts with greater ESG-related experience, training, or commitment should possess superior greenwashing detection abilities through multiple mechanisms: more developed cognitive frameworks for understanding sustainability concepts, enhanced pattern recognition from exposure to various greenwashing techniques, increased skepticism motivated by personal investment in sustainability issues, and access to specialized information networks.

RQ3: How do experts' characteristics influence contradictory identification and washing detection capabilities?

H3a: ESG-related personal traits positively correlate with contradiction identification abilities; H3b: ESG-specific expertise enhances greenwashing detection more than digital washing detection. Once again, this is also tested for the digital domain.

Research Question 4: Comprehensive Trait Effects on Investment Recommendations

The final research question integrates the previous components into a comprehensive model that examines how expert traits influence investment recommendations by identifying potential washing mechanisms. This framework acknowledges that expert traits can impact investment outcomes through both direct pathways (systematic preferences- in this case, the framing that they received as the first screen) and indirect pathways (enhanced analytical capabilities). The distinction between these pathways has important implications for understanding the value of ESG expertise. If effects operate primarily through direct preferences, expert recommendations might reflect personal values rather than analytical advantages. However, if expertise translates into superior greenwashing identification and higher risk assessment, expert recommendations will represent analytical value.

RQ4: How do experts' characteristics influence investment recommendations through washing identification mechanisms

H4a: ESG-related traits positively correlate with washing identification capabilities; H4b: ESG traits influence investment recommendations both directly and indirectly through enhanced greenwashing identification, with identification mediating the expertise-investment relationship.

This research design advances sustainable finance literature through three key contributions. First, by comparing ESG and digital domains, we isolate domain-specific cognitive processes from general analytical capabilities. Second, our systematic progression from (visual) attention to Identification to investment outcomes maps the cognitive pathway underlying expert decision-making, considering also personal traits. Third, our dual-hypothesis structure enables assessment of both universal cognitive mechanisms and domain-specific enhancements, providing insights into both theoretical processes and practical applications. These research questions collectively address how financial experts navigate complex ESG information environments, with implications for market efficiency, investment performance, and regulatory policy in sustainable finance.

3. Methodology

3.1 Research Design and Pre-Registration

We employ a between-subjects experimental design combining eye-tracking technology with survey-based behavioral measurements to investigate greenwashing detection mechanisms in the banking sector. The research was pre-registered prior to data collection; see https://aspredicted.org/see_one.php.

Figure 2: Experiment Stages

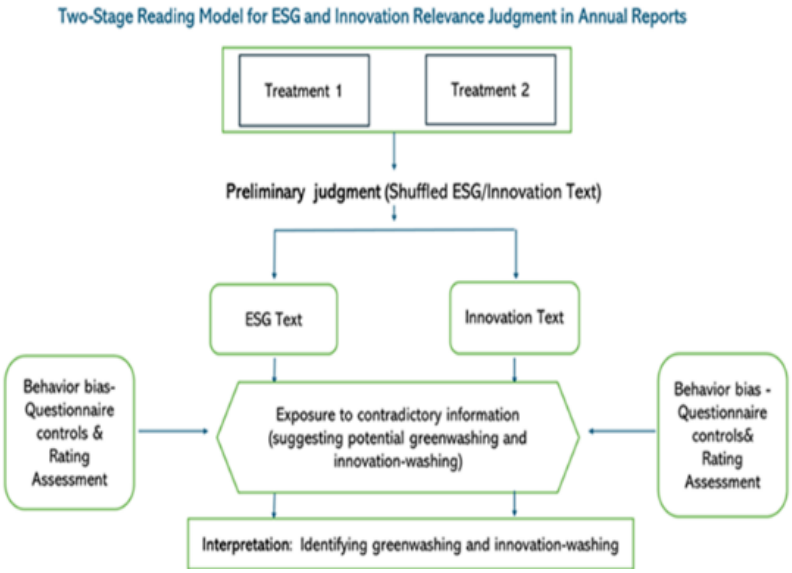


***Figure 2 illustrates the two-stage reading model that assesses how financial professionals interpret ESG and innovation content in corporate reports, testing the experimental behavioral model presented in Figure* 1.**

Participants were randomly assigned to either an ESG-framed or an Innovation-framed treatment, with identical financial metrics to isolate framing effects from quality differences (Figure 2). The eye-tracking experiment employed realistic banking communications with embedded inconsistencies between stated commitments and reported actions. Materials were adapted from actual chairperson letters through professional consultation and validated via pilot testing with financial professionals.[5].

[5] We conducted two pilot studies to validate our research design and experimental protocol. The first pilot study, conducted in November 2023 (n=5 financial professionals), tested the online survey instrument and revealed preliminary evidence of the hypothesized relationship between washing detection and investment recommendations. Specifically, participants identified higher levels of greenwashing, which was subsequently associated with lower investment recommendations. The second pilot study, conducted in September 2024 (n=5 financial professionals), validated the complete experimental protocol using mobile eye-tracking laboratory testing with the Tobii Pro Spectrum system. Results confirmed the feasibility of our mobile laboratory setup. They demonstrated that initial framing influences subsequent attention allocation patterns, with participants showing enhanced scrutiny toward contradictions related to their initial exposure condition. These pilot studies validated both the sensitivity of our eye-tracking measures for detecting treatment effects and the overall experimental design before proceeding to the main data collection phase.

Figure 3: Experimental Screens in Tobii Lab

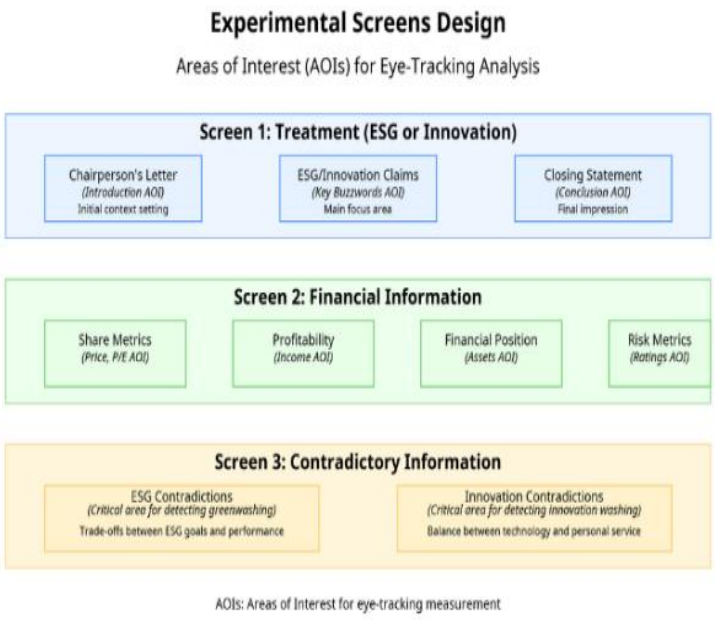


Figure 3 shows a three-screen setup with designated AOIs for eye-tracking, analyzing attention to ESG/Innovation claims, financial data, and contradictory information.

Each screen contains specifically designed Areas of Interest (AOIs) for measuring relative fixation times) carefully designated for measuring attention pattern (figure 3) : (1) Initial Content Exposure: established treatment conditions through chairperson letters emphasizing either environmental sustainability (ESG condition) or digital transformation (Innovation condition) while maintaining equivalent complexity; This screen contains key ESG or innovation buzzwords and claims; (2)Financial Performance Screen: presented identical banking metrics to all participants; (3) Contradictions Screen[6]: revealed information indicating potential washing behaviors through subtly embedded "say-do gaps" with randomized contradiction arrangements (Figure 3).

Measurement approach recognizes that visual attention serves as a window into cognitive processing, with longer visual engagement typically indicating more profound cognitive elaboration and greater information processing effort (Carpenter & Carpenter, 1980; Rayner, 1998). Our primary measure captures the total duration participants spend visually fixating on specific content areas, measured in milliseconds for each Area of Interest (AOI). This absolute measure provides direct evidence of the amount of attention participants allocate to different disclosure sections. However, since individuals vary considerably in their overall reading speed and total time spent viewing materials, we complement this absolute measure with a relative attention metric. The relative fixation measure normalizes attention allocation by calculating the proportion of total viewing time dedicated to each content area. This approach accounts for individual

[6] We simulated a bank chairman's letter to shareholders, based on an annual financial report from a year with good results. The letter drew inspiration from bank samples, focusing on economic conditions and the use of innovation and corporate responsibility terms. Some banks, despite promoting sustainability, were involved in financing the oil and gas industry. To address potential greenwashing, managers might include disclaimers and highlight ESG compliance

differences in processing speed and overall engagement duration, enabling more accurate comparisons across participants with varying reading behaviors.

Post-experiment questionnaires assessed potential washing identification and investment recommendations. We collected information on individual characteristics, habits, knowledge, and beliefs regarding ESG and digital and technological advances in the banking industry (for more details on the design of AOIs and the questionnaire, see Appendix 1).

This three-stage design operationalizes our dual attention mechanism: the treatment directly manipulates external attention allocation by forcing participants to focus systematically on either ESG or digital innovation features. At the same time, eye-tracking measures capture internal attention patterns as participants naturally process the disclosure materials. This approach enables us to examine both how directed attention to specific domains (external manipulation) and spontaneous visual attention patterns (internal measurement) influence contradiction detection and interpretive judgment, while maintaining natural reading patterns through participant-controlled

3.3 Participants and Data Collection

Data collection utilized a Tobii Pro Spectrum eye tracker[7]. A mobile laboratory at participants' workplaces included standardized equipment, consistent lighting, acoustic insulation, and real-time monitoring, enhancing ecological validity while maintaining methodological control. Each 35-minute session included informed consent, calibration, an experimental task, and a post-experimental questionnaire. Eye-tracking quality was consistently high (M = 87.3% tracking ratio, SD = 8.9%), with 94% of participants exceeding 85% tracking[8]. The final sample comprises 128 financial professionals (62 ESG, 66 Innovation condition) from a major Jerusalem-Tel Aviv financial institution (September-November 2024). Table 1 summarizes the sample's statistics.

Table 1: Participant Demographics

Characteristic	Total Sample (N=127)	ESG Condition (n=62)	Innovation Condition (n=65)
Gender			
Male	72 (57.1%)	37 (59.7%)	35 (54.7%)
Female	54 (42.9%)	25 (40.3%)	29 (45.3%)
Age			
20-35 years	33 (26.0%)	17 (27.4%)	16 (24.6%)
36-45 years	41 (32.3%)	17 (27.4%)	24 (36.9%)
46-60 years	49 (38.6%)	25 (40.3%)	24 (36.9%)
61-74 years	4 (3.1%)	3 (4.8%)	1 (1.5%)

[7] Individual 9-point calibration procedures required accuracy deviations <0.5 degrees visual angle. Participants sat 60-65 cm from a 24-inch monitor (1920×1080 resolution) under controlled lighting.

[8] Calibration accuracy averaged 0.48° (SD = 0.21°). Pre-specified exclusion criteria included tracking ratios <40% or calibration errors >0.5 degrees. Questionnaire screening for completion rates <80%, patterned responses, and attention check failures resulted in one participant's exclusion. Systematic integrity checks included range validation, logical consistency testing, and cross-validation between measures. The Hebrew University IRB approved all procedures.

Educational Attainment			
PhD	21 (16.5%)	11 (17.7%)	10 (15.4%)
Master's degree	78 (61.4%)	38 (61.3%)	40 (61.5%)
Bachelor's degree	13 (10.2%)	3 (4.8%)	10 (15.4%)
Undergraduate student	14 (11.0%)	9 (14.5%)	5 (7.7%)
High school	1 (0.8%)	1 (1.6%)	0 (0.0%)
Advanced Degrees (MA/PhD)	99 (77.9%)	49 (79.0%)	50 (76.9%)
Familiarity with ESG reporting standards			
Mean (SD) on 7-point scale	2.6 (1.8)	2.5(1.6)	2.5(1.7)
Major Jerusalem-Tel Aviv financial institution (Total)	127 (100%)	62 (100%)	65 (100%)
Data Collection Period	September-November 2024		

Note: Percentages may not sum to 100% due to rounding. ESG familiarity measured on a 7-point scale, where higher scores indicate greater familiarity.

3.4 Variables and Measurement

Our measurement framework operationalizes the theoretical model by capturing the complete pathway from attention manipulation through cognitive processing to investment decision outcomes. Each variable serves a specific theoretical purpose in testing our hypotheses about the Identification mechanisms for potential greenwashing.

The study's primary outcome measures reflect the two-stage process central to our theoretical framework: identifications of potential washing behaviors and their translation into investment decisions. The questionnaire collects both measures. Potential washing identification represents experts' sensitivity to recognize a potential for deceptive sustainability or innovation practices, measured through multi-item scales assessing perceived transparency, honesty, and consistency of corporate claims. This measurement approach recognizes that potential washing identification involves evaluating the credibility and coherence of corporate communications rather than simply identifying explicit contradictions. The scale design (1 = completely transparent and honest, 7 = highly not) captures the continuum of skepticism that characterizes expert evaluation of potentially deceptive practices. Investment recommendations serve as our ultimate dependent variable, representing the practical outcome of the cognitive processes we examine. Using a 5-point scale (1 = strongly recommend, 5 = strongly recommend against) with the midpoint representing "similar to other banks," this measure captures how potential washing detection translates into actionable investment guidance.

Our secondary dependent variable, attention to contradiction identification (as measured by relative fixation values), provides an objective measure of the cognitive processes underlying the detection of washing (the “internal attention”). Eye-tracking fixation metrics on areas containing contradictory information offer direct evidence of participants' engagement with the comparative analysis necessary for identifying inconsistencies between stated commitments and actual practices. This measure bridges the gap between our theoretical emphasis on attention allocation and the behavioral outcomes reflected in washing identification and investment recommendations.

The treatment condition represents our primary experimental manipulation, operationalizing the "external attention" mechanism central to our theoretical framework. This binary variable (1 = Screen 1 ESG focus version, 0 = Screen 1 Innovation/Digital focus Version) determines whether participants receive directed attention toward sustainability-related or innovation-related content before evaluating corporate ambiguity disclosures in Screen 3. Rather than simply providing contextual framing, this manipulation directly influences cognitive resource allocation by requiring systematic focus on domain-specific information, enabling us to test how directed attention affects subsequent processing of potentially contradictory information.

Expert characteristics represent a complementary component of our theoretical model, as washing identification likely varies systematically based on domain-specific knowledge, experience, and personal orientations. Our comprehensive assessment includes ESG familiarity and sustainable finance literacy measures that capture participants' technical knowledge and experience in sustainability evaluation. Principal component analysis of these individual characteristics yields composite measures that capture the underlying dimensions of expert variation most relevant to washing detection (for the detailed process of creating the components, see Appendix 2)

ESG-related attitudes, perceptions, and behavior: Four components with eigenvalues >1.0 explained 58% of the total variance:

PC1 - Environmental Action Orientation (λ = 2.10): Proactive environmental behaviors, with high loadings on recycling importance (0.78) and sustainable investment practices (0.71);

PC2 - Media and Regulatory Influence (λ = 1.34): External information influences, with high loadings on media influence (0.82) and regulatory impact awareness (0.69).

PC3 - Governance and ESG Data Engagement (λ = 1.21): ESG data engagement (0.75), supply chain considerations (0.68), and board diversity importance (-0.54).

PC4 - Climate Risk and Economic Evaluation (λ = 1.16): Climate risk awareness (0.79) and economic evaluation of environmental factors (0.72).

Digital–related attitude, perception, and behavior:

Three components explaining 65.1% of total variance：

PC1 - Digital-Technological Tendency (26.05% variance): Technology usage (0.64) and fintech knowledge (0.66). Represents technological orientation and expertise, capturing adoption tendencies and knowledge of financial technology.

PC2- Digital-Cyber and Innovation Identification (22.04% variance): Cyber rating (0.62) and innovation rating (0.39). Reflects a critical assessment of cyber risks and innovation claims, representing potential capabilities for identifying digital washing.

PC3- Digital-Operational Risk Importance (17.00% variance): Innovation rating (0.69) and operational risk importance (0.64). Captures innovation-operational risk relationships, reflecting awareness of the impact of technological innovations on organizational risk profiles.

Personal and Demographic Characteristics

The analysis included eight variables representing demographic characteristics (age group, marital status, number of children), risk orientation measures (general risk-taking, financial risk-taking), and economic risk perception indicators (governance pricing, technological risk pricing, interest rate pricing). The varimax rotation revealed a clear component structure where each variable loaded primarily on a single component, facilitating straightforward interpretation. Together, these three components explained 69.3% of the total variance in the individual characteristics.

PC1 - Risk Orientation: This component was defined by strong loadings from general risk-taking (loading = 1.00) and financial risk-taking (loading = 1.00), representing individuals' tolerance for uncertainty in both general and financial contexts.

PC2- Demographic Maturity: This component captured life stage and family structure variables, with primary loadings from marital status (loading = 1.00), age group (loading = 1.00), and number of children (loading = 1.00), reflecting personal and family maturity dimensions.

PC3 - Economic Risk Perception: This component was characterized by loadings from the economic risk pricing variables, including governance pricing (loading = 1.00), technological risk pricing (loading = 1.00), and interest rate pricing (loading = 1.00), capturing awareness and evaluation of macroeconomic and institutional risks.

To facilitate subsequent analyses, we converted the continuous component scores into categorical variables using quantile-based thresholds[9]. Gender was retained as a separate binary variable outside the component structure to examine its independent influence on contradiction detection patterns and washing identification, as it did not load meaningfully on any of the extracted components and represents a theoretically distinct individual difference dimension.

3.5 Descriptive Statistics

AOI fixation durations varied across screens. Screen 1 averaged 12.4 seconds (SD = 6.8) for ESG content and 11.7 seconds (SD = 5.9) for Innovation content. Screen 3 contradiction areas fixations: ESG 8.3 seconds (SD = 4.2), Innovation 7.9 seconds (SD = 3.8). Participants allocated similar attention proportions to ESG content (M = 0.56, SD = 0.12) and innovation content (M = 0.59, SD = 0.13) on Screen 1. Lower relative fixation durations for contradictory information on Screen 3 (ESG: M = 0.21, SD = 0.09; Innovation: M = 0.19, SD = 0.08) suggest participants processed these sections holistically rather than focusing on isolated elements. This holistic reading pattern indicates participants integrated contradictory information within a broader context, particularly relevant for detecting 'washing' practices. We incorporated this into our high-attention pattern variable design. (Appendix 1 Figure….)

Table 2 presents descriptive statistics across treatment conditions. Participants demonstrated moderate levels of washing identification (greenwashing: M = 3.45, SD = 1.21; digital washing: M = 3.08, SD = 1.18)

[9] For the Risk Orientation and Demographic Maturity components, we established three categories (Low, Medium, High) with relatively balanced distributions. The Risk Orientation component showed the following distribution: Low (37.5%), Medium (30.4%), High (32.1%). The Demographic Maturity component was displayed as follows: Low (36.6%), Medium (32.1%), and High (31.3%). The Economic Risk Perception component initially showed an imbalanced three-category distribution, necessitating reclassification into a binary structure to ensure analytical robustness. The final binary categorization yielded: Low Economic Risk Perception (46.4%) and High Economic Risk Perception (50.0%), with the remaining 3.6% representing missing values.

on a seven-point scale. Investment recommendations averaged 2.87 (SD = 0.95), indicating a conservative approach to attitudes toward presented scenarios.

Table 2: Descriptive Statistics by Treatment Condition

Variable	ESG Treatment	Innovation Treatment	t-test Results
	Mean (SD)	Mean (SD)	t(df), p-value, Cohen's d
Washing Identification			
Greenwashing Identification	3.44 (1.22)	3.41 (1.29)	t(125) = -0.15, p = .881, d = -0.03
Digital Washing Identification	3.18 (1.21)	2.91 (1.24)	t(126) = -1.24, p = .217, d = -0.22
Investment Recommendation	3.08 (0.82)	3.20 (1.02)	t(124) = 0.71, p = .477, d = 0.13

Note: n = 59-62 (ESG), n = 63-66 (Innovation). All scales: 1-7 (washing identification), 1-5 (investment recommendation, reversed). Higher scores indicate greater washing identification and stronger investment recommendations.

For testing purposes, variables were also reconstructed at high and low levels, which were determined using a median split. Binary variables show balanced initial attention allocation (50% high fixation across treatments), but domain-specific effects appeared: participants paid more attention to contradictions in non-primed domains (Innovation treatment: 50% ESG contradiction fixation vs. 39% in ESG treatment; ESG treatment: 60% Innovation contradiction fixation vs. 53% in Innovation treatment) (Table 3).

Table 3: Attention Allocation (%)

Binary Variable	ESG Treatment	Innovation Treatment
High Greenwashing Identification	47%	44%
High Digital Washing Identification	37%	27%
High ESG Contradiction Fixation	39%	50%
High Innovation Contradiction Fixation	60%	53%

Note: n = 62 (ESG), n = 66 (Innovation). Binary variables are created via median splits.

These attention patterns indicate that attentional shifts toward unexpected domain-participants scrutinize unfamiliar content more intensely when detecting inconsistencies. While initial attention was balanced, experimental framing influenced subsequent processing, particularly in areas such as contradiction detection and risk assessment. Results demonstrate domain-specific cognitive processing rather than general analytical responses.

4. Results

4.1 RQ1: Attention Patterns and Washing Detection

RQ1 examined whether financial experts' attention to content affects their probability of identifying potential washing. Consistent with H1a, we found significant positive relationships between attention allocation and detection, though effects were domain-specific.

Screen 1 fixation and framing affects (RQ1)

Higher ESG fixation during Screen 1 significantly enhanced the identification of potential greenwashing. Participants with high fixation levels on ESG content demonstrated substantially greater potential greenwashing detection scores compared to those with low fixation levels (M = 3.77 vs. M = 3.13; t(60) = 2.10, p = 0.040, Cohen's d = 0.54) . This medium effect suggests that early ESG attention ("external attention" path) reliably predicts subsequent potential washing detection, supporting the role of selective attention in financial decision-making (Hirshleifer & Teoh, 2003). However, this pattern was ESG-specific. In the Innovation treatment, although participants showed a numerically higher potential for digital washing identification, this difference was not statistically significant. This asymmetry suggests that detecting potential greenwashing requires more sustained external attention than detecting potential digital washing, possibly reflecting financial professionals' greater familiarity with assessing environmental claims. Furthermore, Attention to digital content showed no significant effects on washing detection in either domain. Neither ESG nor Innovation treatment conditions produced significant differences in washing identification based on innovation content fixation levels, with all effect sizes remaining small (Cohen's d < 0.30) and non-significant (all p > 0.30) (Table 4, see Figures in Appendix 3).

Table 4: Attention Patterns and Potential Washing Identification by Screen 1 Treatment Condition

Treatment Condition	Outcome Measure	High Fixation Screen 1	Low Fixation Screen 1	Difference	t-statistic	p-value	Cohen's d
		M (SEM)	M (SEM)				
ESG Treatment	Potential Greenwashing Id.	3.77 (0.18)	3.13 (0.17)	0.64	2.10	0.040*	0.54
Innovation Treatment	Potential Greenwashing Id.	3.58 (0.20)	3.24 (0.19)	0.34	1.05	0.297	0.28
ESG Treatment	Potential Digital Washing Id.	3.32 (0.21)	3.03 (0.20)	0.29	0.95	0.348	0.24
Innovation Treatment	Potential Digital Washing Id.	3.03 (0.23)	2.79 (0.22)	0.24	0.79	0.430	0.20

Note: High and low fixation levels were determined using a median split of relative fixation time on respective content areas during Screen 1 exposure, with washing detection measured on a 7-point scale, where higher scores indicate greater detection of potential washing behaviors. Error bars represent ±1 SEM. * p < 0.05. Detailed individual comparisons are presented graphically in Appendix 3.

Attention to Contradiction and Screen 1 Treatment Manipulation (RQ1)

Table 5: Screen 1 Treatment Effects on Contradiction Detection and Attention Allocation

Variable	**Innovation Treatment**	**ESG Treatment**	**Difference**	**t-statistic**	**p-value**	**95% CI**
	M (SE)	M (SE)				
Contradiction Detection						
High ESG Contradiction	0.500 (0.062)	0.387 (0.062)	0.113	1.28	0.202	[-0.061, 0.287]
High Innovation Contradiction	0.530 (0.062)	0.597 (0.063)	-0.066	-0.75	0.453	[-0.241, 0.108]
Screen 3: Attention Allocation						
Relative ESG Attention	0.491 (0.012)	0.468 (0.015)	0.022	1.17	0.244	[-0.015, 0.060]
Relative Innovation Attention	0.448 (0.012)	0.453 (0.014)	-0.005	-0.27	0.784	[-0.040, 0.030]

Note: Difference calculated as Innovation Treatment minus ESG Treatment. All comparisons are non-significant (p > 0.05). CI = Confidence Interval.

The analysis in Table 5 reveals no significant differences between ESG and Innovation treatment conditions across all measured variables. While participants in the Innovation treatment showed numerically higher rates of ESG contradiction detection (50% vs. 38.7%), this difference was not statistically significant (p = 0.202). Conversely, ESG treatment participants showed slightly higher rates of Innovation contradiction detection, although this difference was again non-significant (p = 0.453). Attention allocation patterns in Screen 3 were remarkably similar between treatment groups, with negligible differences in both ESG attention (p = 0.244) and Innovation attention (p = 0.784). These findings suggest that the initial treatment manipulation did not create lasting differences in general contradiction detection capabilities or overall attention allocation patterns, supporting the specificity of our main experimental effects.

Expert Traits and Attention to Contradiction (RQ1&RQ3)

Table 6: Logistic Regression Predicting ESG Contradiction Detection

Variable	Coefficient (β)	SE	Odds Ratio	95% CI	p-value
Attention and Treatment					
High Screen 1 Fixation	2.04*	0.89	7.71	[1.35, 43.99]	0.022
ESG Treatment	0.90	2.74	2.46	[0.01, 656.71]	0.742
Fixation × ESG Treatment	-0.80	1.31	0.45	[0.03, 6.12]	0.543
Environmental Orientation (PC1)					
Medium (ref: Low)	1.70†	0.99	5.48	[0.79, 38.01]	0.084
High (ref: Low)	2.81*	1.32	16.66	[1.27, 218.91]	0.032
Media & Regulatory Awareness (PC2)					
Medium (ref: Low)	-0.10	0.98	0.90	[0.13, 6.18]	0.916
High (ref: Low)	1.52	1.10	4.59	[0.53, 39.51]	0.166
Key Interactions					
High PC1 × ESG Treatment	-2.50	1.86	0.08	[0.002, 3.31]	0.178
High Risk Perception × ESG	-2.34†	1.19	0.10	[0.01, 1.08]	0.049
Model Fit Statistics					
N	108				
Pseudo R^2	0.223				
LR χ^2	33.18				0.318

Note: Table shows selected key variables from the full model. Reference categories: Low for PC components, No ESG treatment, Low risk perception. SE = Standard Error; CI = Confidence Interval. † p < 0.10, * p < 0.05, ** p < 0.01. Full model includes additional PC components (PC3-PC4), demographic controls, and risk-taking measures not shown for clarity.

Analysis of expert characteristics and ESG contradiction detection revealed complex patterns that may have different interpretation (Appendix 4A). Initial ANOVA analyses across four principal components showed no significant direct effects on attention allocation to contradictory information (all p > 0.326, R^2

< 0.018). However, comprehensive regression analyses unveiled important relationships operating through indirect pathways. The most striking finding emerged from multivariate logistic regression: high relative fixation on Screen 1 became a significant predictor of ESG contradiction detection only when individual characteristics were controlled for (OR = 7.71, 95% CI [1.35, 43.99], $p < 0.05$). This suggests that initial attention allocation serves as a critical mediating mechanism; however, its effect is masked when individual differences are not accounted for. Environmental Action Orientation (PC1) demonstrated the strongest relationship with the detection of contradictions (attention). Participants with high environmental orientation showed substantially higher odds of identifying ESG contradictions (OR = 16.66, 95% CI [1.27, 218.91], $p < 0.05$) compared to those with low orientation. This effect only emerged in comprehensive models, indicating that environmental values enhance sensitivity to ESG-related contradictions through complex interactions with other characteristics rather than simple direct effects. Despite a non-significant overall model fit ($\chi^2(29) = 33.18$, $p = 0.318$), the moderate pseudo-R^2 of 0.223 suggests that the model explains meaningful variance. The interaction between high-risk perception and ESG treatment approached significance with a substantial negative coefficient ($\beta = -2.34$, $p < 0.10$), indicating that heightened risk awareness may paradoxically impair contradiction detection in ESG contexts—possibly reflecting overcautious processing that misses subtle inconsistencies.

Expert Traits and Attention to Digital Innovation Contradiction (Appendix 4B); Digital expertise components showed distinct patterns from ESG characteristics. ANOVA results revealed Digital-Cyber and Innovation Identification (PC2) as the most promising predictor, approaching significance ($F(2, 126) = 2.81$, $p = 0.064$, $R^2 = 0.043$). Medium cyber-innovation awareness demonstrated optimal detection rates ($M = 0.635$, $p < 0.001$), suggesting an expertise "sweet spot" for critical evaluation. Linear regression models consistently showed weak explanatory power (maximum $R^2 = 0.174$, all $p > 0.932$). However, logistic regression revealed noteworthy effects despite a non-significant overall fitness. Medium PC2 emerged as a significant predictor across models (Model 4: $\beta = 2.086$, $SE = 1.064$, $p < 0.05$), indicating participants with moderate digital-cyber awareness were approximately 8 times more likely to detect innovation contradictions compared to low awareness levels. Complex interaction patterns emerged uniquely in the innovation domain. High perceived risk showed significant negative effects ($\beta = -2.028$, $p < 0.05$), while its interaction with ESG treatment was significantly positive ($\beta = 2.745$, $p < 0.05$). Additionally, gender interactions appeared only in innovation detection, with males in ESG conditions showing higher contradiction identification ($\beta = 2.540$, $p < 0.05$), suggesting domain-specific processing differences.

These findings support partial validation of our hypotheses regarding expert characteristics and contradiction detection. H3a receives qualified support: digital expertise shows direct positive effects on innovation ambiguity attention, while ESG expertise demonstrates complex, context-dependent effects. The domain specificity of these relationships suggests expertise can both enhance and impair critical evaluation, depending on whether the domain creates cognitive biases (ESG) or enhances analytical capability (digital).

Three key insights emerge: First, the relationship between initial attention allocation and Attention to contradiction is complex, becoming apparent only when individual characteristics are controlled. Second, optimal expertise levels, particularly medium digital awareness, may outperform high expertise due to the avoidance of overconfidence biases. Third, while individual characteristics exhibit limited direct effects on attention allocation, they influence detection capabilities through complex pathways involving interactions between traits, attention patterns, and contextual factors, as demonstrated in the following sections.

Contradiction-Specific Attention Effects on Potential Washing Identification (RQ1&RQ4)

Table 7: Attention to Ambiguity Areas in Screen 3 and Potential Washing Detection by Screen 1 Treatment

Screen 1 Treatment	Screen 3 Ambiguity Area	Washing Detection Type	High Fixation	Low Fixation	Difference	p-value	Cohen's d
			M (SEM)	M (SEM)			
ESG Treatment	ESG Ambiguity	Potential Greenwashing Id.	3.92	3.09	0.84	0.007**	0.73
Innovation Treatment	ESG Ambiguity	Potential Greenwashing Id.	3.51	3.28	0.24	0.461	0.21
ESG Treatment	Innovation Ambiguity	Potential Digital Washing Id.	3.32	3.06	0.26	0.399	0.21
Innovation Treatment	Innovation Ambiguity	Potential Digital Washing Id.	3.03	2.76	0.27	0.386	0.22

Note: High and low fixation levels were determined using a median split of relative fixation time on specific ambiguous content areas (ESG or Innovation) during Screen 3 exposure. Washing detection measured on 7-point scales where higher scores indicate greater detection of potential washing behaviors. ** p < 0.01. SEM values not available for all conditions.

One can observe from Table 7 that the relationship between attention and potential washing identification strengthened when contradiction attention is higher (Screen 3). ESG treatment participants with higher fixation on ambiguous ESG content showed substantially higher potential greenwashing identification (M = 3.92 vs. M = 3.09; t(60) = 2.78, p = 0.007, Cohen's d = 0.73). This significant effect aligns with dual-process theories, suggesting that attention to contradictory information enhances the systematic processing of potential deception cues and plays a crucial role in identifying potential "washing" by experts. Conversely, Innovation treatment showed no significant Screen 3 attention differences, with potential digital washing identification unrelated to Innovation contradiction fixation across conditions (all p > 0.38). This pattern suggests fundamental differences in how financial experts process environmental versus technological claims, potentially reflecting varying domain expertise or established evaluation frameworks (see also Figures in Appendix 5).

These results provide partial support for H1a and H1b. The positive relationship between attention to ambiguity and contradictions and potential washing identification was explicitly confirmed for the detection of potential greenwashing, with more potent effects when ESG content was emphasized before (in screen 1). However, the absence of significant effects for potential digital washing suggests that H1b's prediction of enhanced relationships under domain emphasis applies selectively rather than universally.

Expert Traits and Washing Identification: Progressive Model Analysis

RQ4 examined how expert characteristics influence the attention-detection-recommendation pathway identified in our experimental findings. While our primary focus remains on the experimental manipulation of attention and its effects on washing detection, we conducted comprehensive regression analyses using increasingly complex models to understand how individual differences moderate these core relationships (detailed results in Appendices 5A and 5B).

Greenwashing Identification

Four progressively complex models revealed evolving patterns in predictors of greenwashing identification (see Tables 8 and 9 for full model specifications). Model 1, which examined only attention measures, revealed a marginally significant positive relationship between high fixation on ESG contradictions and greenwashing identification ($\beta = 0.822$, $p < 0.10$). However, the model's limited explanatory power ($R^2 = 0.082$) indicated substantial unexplained variance.

Model 2, incorporating ESG trait components, substantially improved model fit ($R^2 = 0.257$, $F = 1.95$, $p < 0.05$). Media and Regulatory Influence (PC2) emerged as a significant negative predictor, with medium ($\beta = -0.795$, $p < 0.10$) and high ($\beta = -0.664$, n.s.) awareness associated with lower identification rates, demonstrating the "skepticism paradox". Notably, the attention-detection relationship attenuated ($\beta = 0.662$, n.s.), suggesting partial mediation by trait components. The simplified Model 2 results are presented in Table 8, with full interaction terms detailed in Appendix 5A.

Model 3, which included demographic factors, further enhanced the explanatory power ($R^2 = 0.394$). The adverse effects of PC2 strengthened considerably (medium: $\beta = -1.208$, $p < 0.05$; high: $\beta = -1.327$, $p < 0.01$), while Climate Risk Evaluation (PC4) showed positive trends approaching significance (high: $\beta = 1.213$, $p < 0.10$). The demographic category emerged as a strong negative predictor (medium: $\beta = -1.236$, $p < 0.01$), indicating socioeconomic influences on washing detection.

Model 4, incorporating gender, showed a slight reduction in explanatory power ($R^2 = 0.373$) and lost overall significance ($p = 0.122$), suggesting potential overfitting. Gender showed no significant main effect ($\beta = 0.499$, n.s.), though core patterns from Model 3 persisted.

Logistic regression analyses provided additional insights through examination of non-linear relationships (see Appendix 5A, Tables 3-4 for complete logistic regression results). Model progression showed increasing pseudo-R^2 from 0.037 to 0.484. Remarkably, high ESG contradiction fixation became significant only in Model 3 ($OR = 17.79$, $p < 0.05$), suggesting suppressor effects. PC2 demonstrated dramatically stronger negative effects in logistic models (medium: $OR = 0.02$, $p < 0.05$; high: $OR = 0.01$, $p < 0.05$), while PC4 showed extreme positive effects (medium: $OR = 48.37$, $p < 0.05$; high: $OR = 164.86$, $p < 0.05$). Complex interactions emerged, particularly between PC3 and ESG Version ($OR = 84.74$, $p < 0.05$), as detailed in Appendix 5A, Table 3.

Visual representations of trait-identification relationships across experimental conditions are presented in Appendix 5A, Figures 1a-h, revealing distinct patterns for each principal component.

Table 8: Multiple Regression Analysis Predicting Greenwashing Identification

Variable	Model 1	Model 2*
Attention Measures		
Total Relative Fixation on ESG Contradictions	2.162** (1.021)	2.276* (1.215)
ESG Components		
PC1: Environmental Action Orientation (Medium)		-0.255 (0.461)
PC1: Environmental Action Orientation (High)		-0.307 (0.530)
PC2: Media and Regulatory Influence (Medium)		-0.858* (0.483)

PC2: Media and Regulatory Influence (High)		-1.085** (0.521)
PC3: Governance and ESG Data Engagement (Medium)		0.234 (0.507)
PC3: Governance and ESG Data Engagement (High)		-0.171 (0.544)
PC4: Climate Risk and Economic Evaluation (Medium)		0.316 (0.503)
PC4: Climate Risk and Economic Evaluation (High)		0.965 (0.622)
Experimental Condition		
ESG Version		-0.825 (0.968)
Control Variables		
Demographic Category		0.011 (0.165)
Risk-Taking Category		0.153 (0.153)
Risk Perception Category		0.029 (0.231)
Constant	2.389*** (0.502)	2.284** (1.042)
Model Statistics		
Observations	127	112
R^2	0.035	0.237
Adjusted R^2	0.027	0.059
F-statistic	4.48**	1.33

Note: Table presents linear regression coefficients with standard errors in parentheses. Model 1 includes total fixation on ESG contradictions as the sole predictor. Model 2* includes all ESG-related personality components, experimental condition, and control variables. Interaction terms between each component and ESG Version are included in Model 2* but not displayed individually for clarity. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 9: Multiple Regression Analysis Predicting Potential Greenwashing Identification

Variable	Model 1	Model 2	Model 3	Model 4
Attention Measures				
High Fixation on ESG Contradiction	0.212 (0.299)	0.254 (0.300)	0.291 (0.333)	0.124 (0.354)
ESG Version	-0.250 (0.289)	-1.349 (0.841)	-2.123† (1.120)	-1.432 (1.224)
High Contradiction × ESG	0.822† (0.438)	0.662 (0.444)	0.500 (0.503)	0.077 (0.519)
ESG Components				
PC2: Media Influence (Medium)		-0.795† (0.428)	-1.208* (0.490)	-1.217* (0.513)
PC2: Media Influence (High)		-0.664 (0.448)	-1.327** (0.507)	-1.222* (0.522)
PC4: Climate Risk (Medium)		-0.100 (0.418)	0.947† (0.525)	0.919† (0.544)
PC4: Climate Risk (High)		0.500 (0.518)	1.213† (0.617)	1.217† (0.658)
Demographics				

Demographic Category (Medium)			-1.236** (0.444)	-1.321** (0.477)
Perception Risks Category (Very High)			1.455 (0.906)	1.603† (0.923)
Gender (Male)				0.499 (0.384)
Constant	3.303*** (0.211)	4.182*** (0.542)	4.347*** (0.806)	3.965*** (0.890)
Model Statistics				
Observations	127	127	112	111
R^2	0.082	0.257	0.394	0.373
F-statistic	3.65*	1.95*	1.68*	1.39
Prob > F	0.015*	0.017*	0.034*	0.122

Note: Standard errors are in parentheses. † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Digital Washing Identification

Digital washing identification models revealed distinct patterns from those used for greenwashing detection (see Appendix 5B, Tables 1-2 for complete model specifications). Model 1 showed no significant relationship between innovation contradiction fixation and digital washing identification (β = 0.322, n.s.), with minimal explanatory power (R^2 = 0.020).

Model 2, adding digital trait components, revealed modest improvements (R^2 = 0.088) despite non-significant overall fit. Digital-Technological Tendency (PC1) exhibited positive trends at high levels, while Digital-Cyber Identification (PC2) showed consistent negative effects across categories, although not reaching significance in linear models (Appendix 5B, Table 1).

Model 3, incorporating demographics, substantially improved model fit (R^2 = 0.253, F = 1.05, p = 0.076). PC1's positive effect for high technological tendency became significant (β = 0.357, p < 0.05), while PC2 maintained negative trends (medium: β = -1.040, n.s.). Demographic categories showed negative but non-significant effects.

Model 4 maintained similar explanatory power (R^2 = 0.273) but did not improve model significance, with gender showing no meaningful contribution to the linear model.

Logistic regression models for digital washing revealed patterns obscured in linear analyses (Appendix 5B, Table 2). High innovation contradiction fixation showed significant negative effects in complex models (β = -0.131, p < 0.05), indicating that contradiction detection may paradoxically impair washing identification. PC2 medium level significantly predicted lower identification (β = -2.524, p < 0.05), suggesting an "innovation bias" where moderate cyber expertise inhibits critical evaluation. Gender showed marginal positive effects (β = 0.953, p < 0.10) in logistic models despite null effects in linear analyses.

ANOVA results examining digital trait components across experimental conditions are presented in Appendix 5B, Figures 1-7, also demonstrating the "skepticism paradox," where higher digital-cyber awareness is associated with lower washing identification.

These supplementary analyses provide important context for understanding the boundary conditions of our experimental findings while maintaining the core attention-detection mechanism results.

4.2 Potential Washing Identification and Investment Recommendations (RQ2&RQ4)

RQ2 examined the potential correlation between washing and investment recommendations. Consistent with H2a, high-potential greenwashing identification (defined using a median split) resulted in significantly lower recommendations across conditions, although the magnitude of this effect varied by context.

Table 10: Impact of Washing Identification on Investment Recommendations

Treatment Condition	Washing Type	Low Identification	High Identification	Difference	t-statistic	p-value	Cohen's d	Effect Size
ESG Treatment								
	Greenwashing	3.12	2.64	-0.48	2.38	0.020*	0.61	Medium
	Digital Washing	2.98	2.78	-0.20	0.93	0.358	0.24	Small (n.s.)
Innovation Treatment								
	Greenwashing	3.36	2.31	-1.05	4.17	<0.001***	1.17	Large
	Digital Washing	3.28	2.47	-0.81	3.05	0.003**	0.80	Large

Note: Investment recommendations are measured on a scale where higher scores indicate more positive recommendations. High and low identification groups are determined using median split. Negative differences indicate that high washing identification leads to lower investment recommendations. n.s. = not significant. * p < 0.05, ** p < 0.01, *** p < 0.001.

A series of t-tests, as demonstrated in Table 10 and visualized in Annex 6, exhibit that ESG treatment participants with high potential greenwashing identification provided lower recommendations (M = 2.64 vs. M = 3.12; t(60) = 2.38, p = 0.020, Cohen's d = 0.61). This medium-to-large effect suggests that successful detection has a meaningful impact on conservative investment behavior when environmental claims are salient. Surprisingly, the effects were stronger in the Innovation treatment, where high-potential greenwashing identifiers showed substantial differences (M = 2.31 vs. M = 3.36; t(64) = 4.17, p < 0.001, Cohen's d = 1.17). When primed for innovation, potential environmental washing detection led to powerful adverse reactions, possibly due to heightened skepticism of cross-domain credibility. Potential digital washing identification exhibited domain-matching effects. ESG treatment showed no significant impact (M = 2.78 vs. M = 2.98; t(60) = 0.93, p = 0.358, Cohen's d = 0.24), suggesting minimal impact when environmental considerations dominate. However, Innovation treatment showed significant effects (M = 2.47 vs. M = 3.28; t(64) = 3.05, p = 0.003, Cohen's d = 0.80), indicating that potential digital washing detection substantially influences behavior when properly contextualized.

These findings could be explained by framing effects research (Tversky & Kahneman, 1981), which demonstrates that domain salience moderates potential washing detection effects. Domain-matching patterns suggest financial experts apply different evaluation criteria depending on the emphasized context. Both H2a and H2b received support, though with important differentiation. Potential washing identification led to lower investment recommendations (H2a), and the negative impact was indeed more substantial under conditions emphasizing the ESG domain (H2b). However, the pattern revealed unexpected cross-domain effects, with greenwashing detection showing particularly strong effects in the Innovation condition. This suggests that framing effects may significantly influence the evaluations of financial experts, even when they are presented with identical, contradictory evidence.

Experts' Traits Influence on Investment Recommendations

Table 11: Multiple Regression Analysis Predicting Impact of Potential Greenwashing Identification on Investment Recommendation

Variable	Model 1	Model 2	Model 3	Model 4
High Greenwashing Identification	-1.046*** (0.209)	-1.067*** (0.216)	-1.175*** (0.278)	-1.224*** (0.277)
ESG Version	-0.354† (0.204)	-0.147 (0.588)	-0.017 (0.808)	-0.077 (0.793)
High Greenwashing × ESG	0.561† (0.300)	0.722* (0.327)	0.820* (0.397)	0.934* (0.389)
ESG Components				
PC3: Governance (Medium)		-0.647* (0.310)	-0.916** (0.345)	-1.129*** (0.340)
PC3: Governance (High)		-0.128 (0.338)	-0.329 (0.380)	-0.630† (0.377)
PC3: Governance (Medium) × ESG		0.765† (0.427)	1.289** (0.468)	1.481** (0.454)
PC3: Governance (High) × ESG		0.332 (0.465)	0.854 (0.526)	1.055* (0.516)
PC4: Climate Risk (Medium)		0.722* (0.287)	1.004* (0.397)	1.161** (0.385)
PC4: Climate Risk (High)		-0.138 (0.361)	-0.039 (0.460)	0.258 (0.455)
PC4: Climate Risk (Medium) × ESG		-1.205** (0.413)	-1.495** (0.529)	-1.684*** (0.509)
PC4: Climate Risk (High) × ESG		-0.656 (0.500)	-1.032 (0.629)	-1.323* (0.610)
Demographics & Risk Perception				
Demographic Category (Medium)			-0.403 (0.333)	-0.667* (0.336)
Demographic Category (High)			-0.172 (0.320)	-0.361 (0.314)
Demographic (Medium) × ESG			0.540 (0.460)	0.762† (0.453)
Perception Risks Category (High)			0.218 (0.246)	0.431† (0.247)
Perception Risks (High) × ESG			-0.509 (0.369)	-0.681† (0.362)
Perception Risks (Very High) × ESG			-0.943 (0.925)	-1.242 (0.885)
Gender (Male)				0.294 (0.255)
Gender × ESG				0.051 (0.355)
Constant	3.667*** (0.140)	3.497*** (0.390)	3.885*** (0.605)	3.745*** (0.590)
Model Statistics				
Observations	126	126	110	109
F-statistic	10.23***	3.25***	2.11**	2.27**
Prob > F	0.000***	0.000***	0.004**	0.002**
R^2	0.201	0.368	0.457	0.499
Adjusted R^2	0.181	0.255	0.241	0.279
Root MSE	0.839	0.800	0.786	0.748

Note: The Table presents linear regression coefficients with standard errors in parentheses. PC1 (Environmental Action Orientation), PC2 (Media and Regulatory Influence), PC3 (Governance and ESG Data Engagement), and PC4 (Climate Risk and Economic Evaluation) are principal

components. Interaction terms between each component and ESG Version are included in the model. † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Linear regression models demonstrate a strong, consistent negative relationship between high-potential greenwashing identification and investment recommendations across all models, with the coefficient strengthening from Model 1 (β = -1.046, p < 0.001) to Model 4 (β = -1.224, p < 0.001). This suggests that financial experts who identify high-potential greenwashing significantly downgrade their investment recommendations. The effects remain robust after controlling ESG components, personal characteristics, and gender, indicating that potential greenwashing detection has a direct, independent influence on investment decisions.

The interaction between high-potential greenwashing identification and ESG version shows a significant positive moderating effect that strengthens across models (β = 0.561, p < 0.10 in Model 1 to β = 0.934, p < 0.05 in Model 4). This suggests that while the identification of potential greenwashing generally results in negative revisions to investment recommendations, the effects are partially mitigated under the ESG version condition. When ESG factors are explicitly considered, the negative impact of potential greenwashing on investment recommendations is somewhat reduced.

Among ESG components, PC3 (Governance and ESG Data Engagement) and PC4 (Climate Risk and Economic Evaluation) exhibit particularly significant relationships with revisions in investment recommendations. Medium governance engagement demonstrates a significant negative relationship, strengthening from Model 2 (β = -0.647, p < 0.05) to Model 4 (β = -1.129, p < 0.001). This effect is strongly moderated by the ESG version, with the interaction strengthening across models (β = 0.765, p < 0.10 to β 8= 1.481, p < 0.01), suggesting that governance awareness influences investment recommendations differently depending on the contextual framing.

Medium climate risk awareness (PC4) exhibits a significant positive relationship with investment recommendations, strengthening from Model 2 (β = 0.722, p < 0.05) to Model 4 (β = 1.161, p < 0.01). This effect is strongly negatively moderated by ESG version, with the interaction strengthening across models (β = -1.205, p < 0.01 to β = -1.684, p < 0.001). This suggests that while climate risk awareness typically leads to more favorable investment recommendations, the effect is reversed when ESG factors are explicitly considered.

Additional variables in Model 4 reveal that the medium demographic category exhibits a significant negative relationship with investment recommendations (β = -0.667, p < 0.05), with a marginally significant positive interaction with ESG version (β = 0.762, p < 0.10). Gender does not show significant main or interaction effects, suggesting that gender differences do not substantially influence the relationship between potential greenwashing identification and investment recommendations.

Model fit improves significantly with the addition of predictors, with R^2 increasing from 0.201 in Model 1 to 0.499 in Model 4. All models achieve statistical significance (p < 0.01), indicating that the predictors collectively explain a meaningful amount of variance in investment recommendation revisions.

Potential Digital Washing and Investment Recommendations

Linear regression models revealed a consistent negative relationship between potential digital washing identification and investment recommendations, a relationship that remained robust even after controlling for additional variables. However, the impact of digital washing on investment

recommendations was found to be less robust than that of greenwashing, and the mitigating effect of ESG was weak and unstable in more complex models. These findings suggest that financial experts respond differently to digital washing compared to greenwashing, which influences investment decisions.

For full details on the regression analyses, including all model specifications, please refer to Appendix 6**.**

5. Conclusion: Greenwashing Detection Pathways and Cognitive Mechanisms

Our investigation reveals fundamental insights into how financial experts process corporate communications, with attention patterns and contextual framing emerging as primary drivers of potential "washing" detection capabilities and subsequent investment decisions.

Eye-tracking analysis reveals that attention functions as an independent cognitive mechanism, distinct from personality characteristics and individual traits. Visual attention to contradictions consistently predicts identification success (OR = 4.09, $p < 0.05$), indicating that where experts direct their gaze fundamentally shapes their ability to detect inconsistencies in corporate communications. This finding reveals attention patterns that follow distinct cognitive pathways from evaluative judgment, suggesting that training interventions targeting visual processing may operate through different channels than those addressing critical evaluation skills.

Manipulation of attention emerges as a powerful moderator of both detection capabilities and investment decisions. ESG contextual framing significantly moderates potential greenwashing detection's impact on investment recommendations ($\beta = 0.934$, $p < 0.05$), while this moderating effect proves substantially weaker for potential digital washing contexts ($\beta = 0.563$, $p > 0.10$). Framing effects extend beyond simple presentation differences, fundamentally altering how experts process and integrate contradictory information. Significant interaction effects between individual characteristics and framing conditions (interaction OR = 84.74, $p < 0.05$) demonstrate that identical information can lead to dramatically different evaluation outcomes depending on contextual presentation.

Our findings reveal that the detection of potential greenwashing operates through a fundamentally distinct cognitive pathway. Superior explanatory power of potential greenwashing models ($R^2 = 0.499$, $p = 0.002$) compared to potential digital washing models ($R^2 = 0.312$, $p = 0.227$) reflects not only different content domains but also underlying cognitive architectures. Environmental claims are processed through economic risk frameworks, while digital transformation claims rely more heavily on technological familiarity, suggesting expertise effectiveness varies across domains rather than transferring uniformly.

The translation from Identification to investment recommendations demonstrates systematic asymmetries that amplify attention and framing effects. The identification of potential greenwashing has stronger and more consistent adverse effects on investment recommendations ($\beta = -1.224$, $p < 0.001$) compared to the identification of potential digital washing ($\beta = -0.768$, $p < 0.05$). This asymmetry suggests that cognitive mechanisms underlying attention allocation and framing sensitivity directly influence the perceived financial materiality of different corporate claims.

Individual characteristics reveal counterintuitive patterns that challenge conventional assumptions of expertise. The "skepticism paradox" demonstrates that greater media and regulatory awareness paradoxically reduces sensitivity to specific potential instances of greenwashing (OR = 0.01 for high vs. low awareness, $p < 0.05$). In contrast, climate risk awareness shows robust positive effects (OR = 164.86, $p < 0.05$). An "innovation bias" emerges, where medium digital-cyber awareness inhibits the detection of

potential digital washing ($\beta = -2.524$, $p < 0.05$). Gender effects are contextually dependent, with significant interactions indicating that men and women process sustainability information differently under specific framing conditions.

These findings fundamentally advance our understanding of expert judgment by demonstrating that attention paths through contextual framing serve as foundational cognitive mechanisms that shape all subsequent processing. The independence of attention from personality traits, combined with powerful framing effects, suggests interventions targeting these mechanisms may prove more effective than those focusing solely on domain expertise. For financial education, training programs should prioritize framing awareness. For regulatory policy, findings highlight the critical importance of information presentation standards. This research opens avenues for future investigation into the cognitive architecture underlying expert judgment in increasingly complex corporate communication environments, particularly regarding domain-specific detection mechanisms and optimal combinations of traits, contextual alignment, and information processing capabilities. Given that visual attention patterns and contextual framing emerge as foundational cognitive mechanisms independent of personality traits, these findings have important implications for AI-based analysis of corporate communications. While automated systems may excel at identifying textual contradictions, our results suggest that the domain-specific cognitive pathways and contextual sensitivity required for effective washing detection may necessitate human-AI collaboration rather than full automation, particularly given the expertise paradoxes and framing effects that shape expert judgment in ways that may be difficult to replicate algorithmically.

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Regulatory Frameworks

GRI (Global Reporting Initiative) - https://www.globalreporting.org/

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TCFD (Task Force on Climate-related Financial Disclosures) - https://www.fsb-tcfd.org/ (Disbanded October 2023, now under IFRS Foundation)

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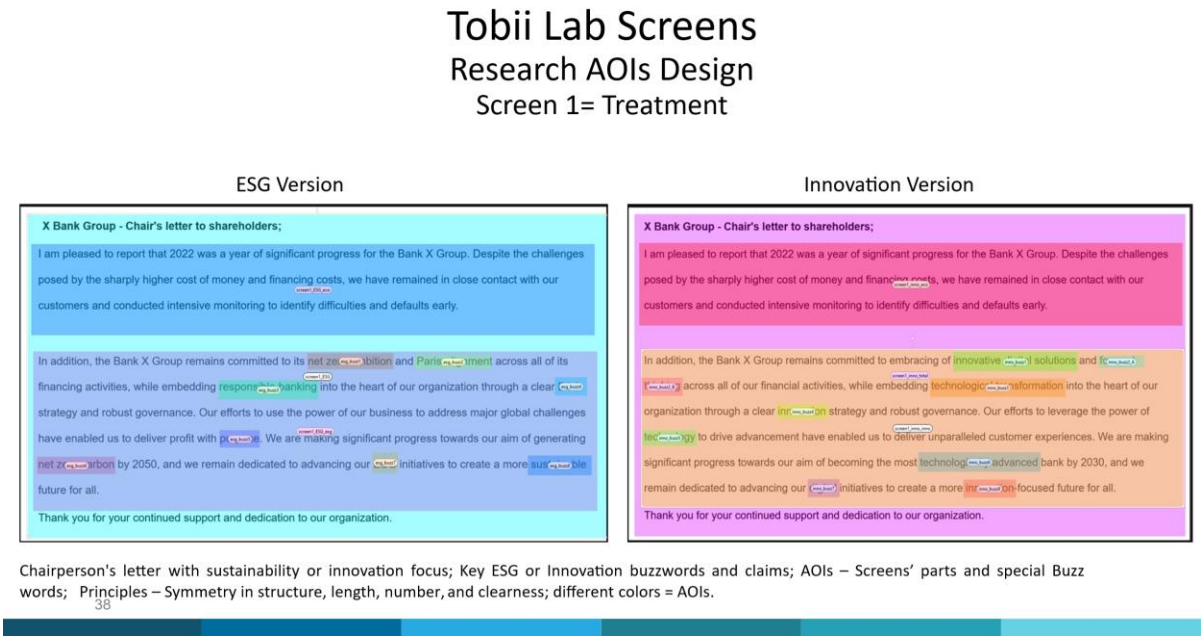
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Appendices

Appendix 1- Expérimente Design and Variables

The Tobii Lab Screens



Chairperson's letter with sustainability or innovation focus; Key ESG or Innovation buzzwords and claims; AOIs – Screens' parts and special Buzz words; Principles – Symmetry in structure, length, number, and clearness; different colors = AOIs.

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Focus point with identical financial information on the bank

Tobii Lab Screens

Research AOIs Design

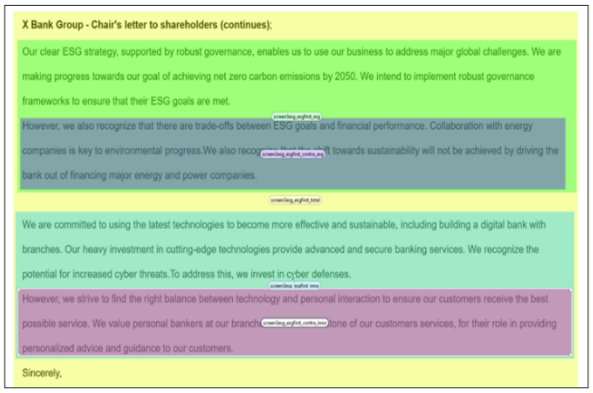
Screen 3(Contradiction Detection)

subject to -Treatment (ESG)

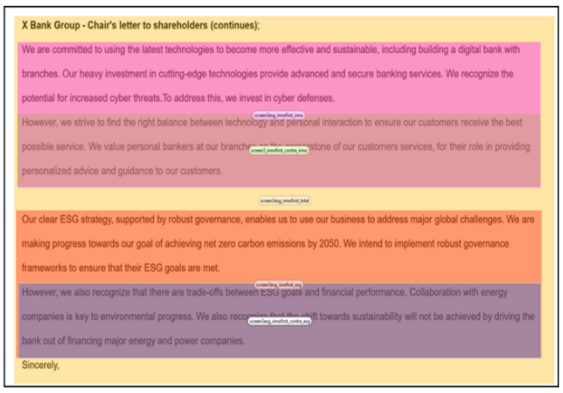
Shuffle

Participant receives 1 out of 2 version

ESG First



Innovation First



40 Information that may contradicts claims from Screen 1. Subtle disclaimers and qualification statements.

Tobii Lab Screens

Research AOIs Design

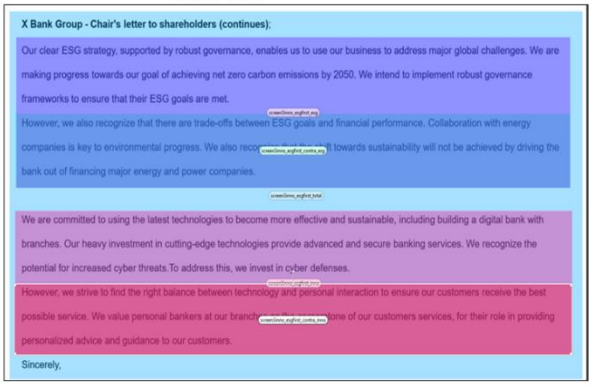
Screen 3(Contradiction Detection)

subject to - Treatment (Innovation)

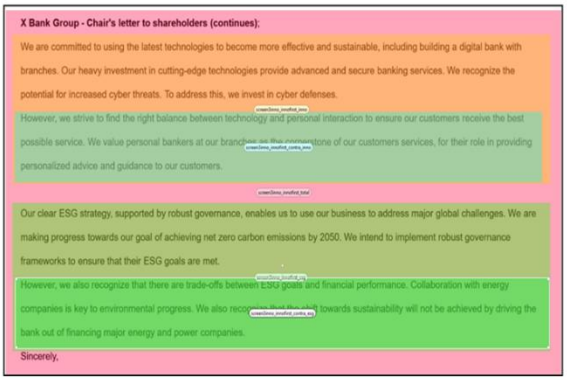
Shuffle

Participant receives 1 out of 2 version

ESG First



Innovation First



41 Information that may contradicts claims from Screen 1. Subtle disclaimers and qualification statements.

<u>Questionnaire Variables and Adjustments</u> :

- General Risk Attitude: "In general, are you a person who is completely willing to take risk or do you try to avoid risk?" This was measured on a 7-point scale (1 = Not willing to take risk, 7 = completely willing to take risk). The same question was also in financial context.
- Importance of risks (reputation, strategic, operational etc.)

ESG-Related Variables

The questionnaire included several items specifically designed to assess participants' ESG-related attitudes and perceptions:

- ESG Risk Pricing Perception: Participants rated the extent to which they believed bank market pricing reflected various risks:
    - Climate-related risks
    - Social-related risks
- Governance-related risks each was rated on a 5-point scale (1 = Very much reflecting, 5 = Not reflecting), with higher scores indicating lower perceived risk reflection in market pricing.
- Investing in sustainable companies enhances the sense of purpose and impact (1 = Strongly agree, 5= strongly disagree); aligns with personal values and beliefs (1= strongly believe, 5 = strongly disbelieve);
- Recycling attitude; importance to you (1= Extremely important, 5 = Not at all important); Belief that it can make significant impact on environment and society (1 = Strongly believe, 5= Do not believe); Practice recycling at home (1= Always, 5= Never); making out of a list the items recycled by the participant on a daily basis.
- Familiarity (Knowledge); familiar with the symbols and signs used to indicate recycled items (1=Definitely yes, 5= Definitely not); How have recent regulatory developments in sustainable finance affected one's investment decisions (1= No impact, 7= Significant impact); Familiarity with ESG standards (1= Not at all, 7= Very familiar)
- Believe in significant for financial performance (list of : climate change mitigation, human rights, board diversity and independence, private data and data security, supply chain management)
- Sources of informaction and reputation risk perception; believe that social media influence market perceptions of company's ESG performance (1= No impact, 7=Significant impact); ESG reliable data sources (1= Company reports, 2= ESG rating, 3= Regulatory reports, 4= Media reports, 5= NGO assessments, 6 = non).

Innovation – Digital Related variables

- Risk Pricing Perception: Participants rated the extent to which they believed bank market pricing reflected various risks:
    - Technological risks

- Knowledge: Understanding of digital currencies and their underlying technology (1= High level of understanding, 5= do not understand)
- Using the latest financial technologies (1= frequently use them, 5= rarely use them)
- Updated on latest regulatory developments in the fintech sector (1= Very actively, 5= Not at all)

To ensure consistent directionality across all ESG-related variables, we examined the original scales and determined that no reversals were necessary as higher values already indicated.

For analytical purposes, we also created several binary variables by dichotomizing continuous measures at their median values:

I. High Greenwashing Identification (high_gw):
II. High ESG Contradiction Identification (high_contra_esg):

Fixation trends:

Figure 1: Total Fixation Duration in Areas of Interest

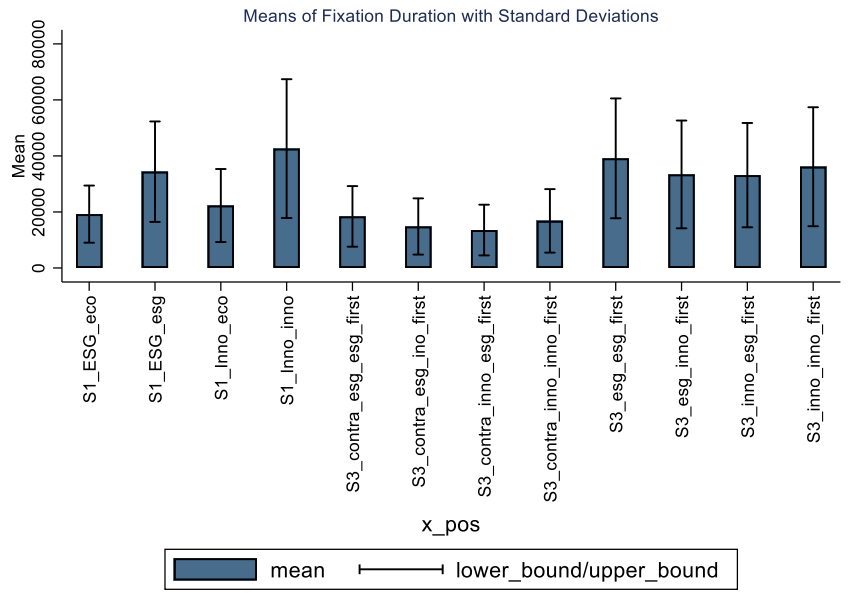
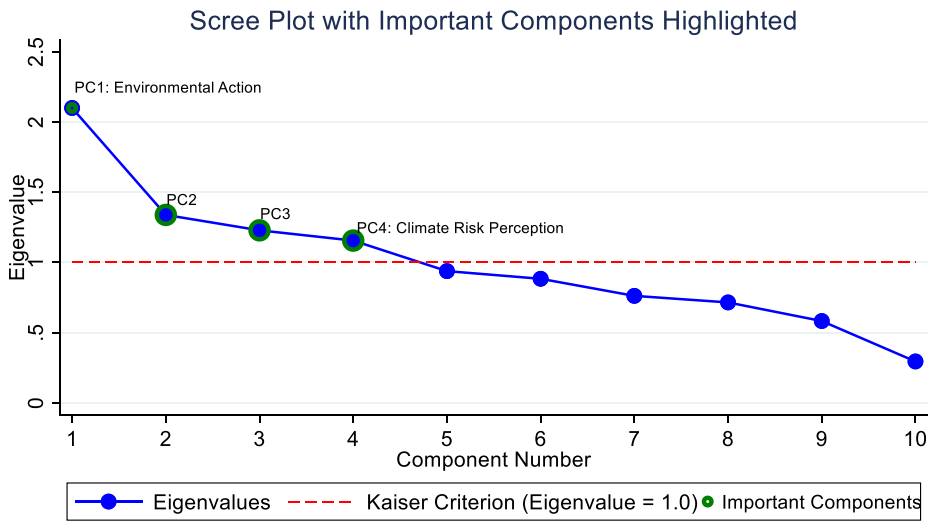


Figure 1: Mean Fixation Durations (ms) with Standard Deviations Across Experimental Conditions. Figure X: Total Fixation Duration in AOIs across Screens 1–3. Figure Y: Mean Fixation Durations (ms) and Standard Deviations by AOI and Treatment Condition. Bars represent mean fixation durations for each area of interest: Screen1 ESG economic content (S1_ESG_eco), ESG sustainability content (S1_ESG_esg), Screen 1 innovation version economic content (S1_inno_eco), Screen 1 innovation technological content (S1_inno_inno), Screen 3 ESG contradiction when ESG paragraph is first (S3_contra_esg_esg_first), Screen 3 ESG contradiction for when innovation paragraph is first (S3_contra_esg_inno_first), innovation contradiction for ESG-first participants (s3_contra_inno_esg_first), Screen 3 innovation contradiction for when innovation paragraph is first participants (S3_contra_inno_inno_first), Screen 3 ESG content for when ESG paragraph is first participants (S3_esg_esg_first), Screen 3 ESG content for when innovation paragraph is first participants (Screen3_esg_inno_first), Screen 3 innovation content for when ESG-paragraph is first participants (Screen3_inno_esg_first), and Screen 3 innovation content for when innovation paragraph is first participants (Screen3_inno_inno_first). Error bars represent ±1 standard deviation. Longer fixation durations indicate greater attentional focus and cognitive processing of the respective content areas.

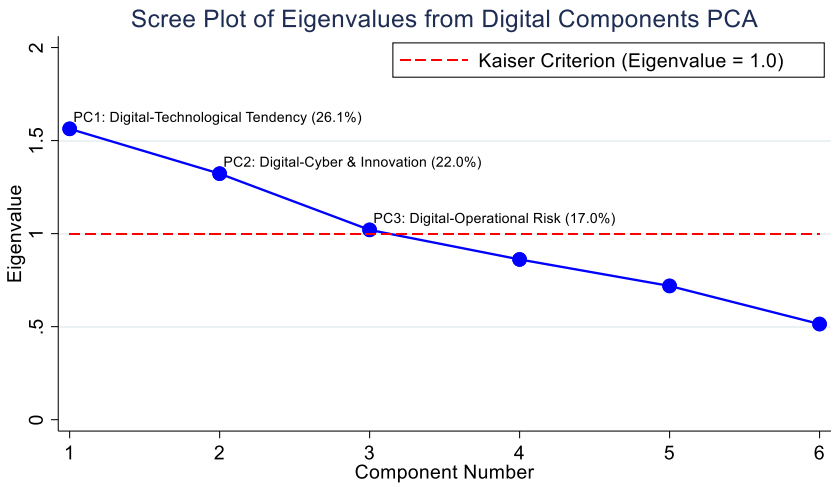
Appendix 2 – Principal Components Variables

Figure 1: Principal Component Analysis of Expert Traits – Sustainability



Note: The scree plot displays eigenvalues for each principal component extracted from the ESG-related variables. The plot reveals four components with eigenvalues exceeding the Kaiser Criterion threshold of 1.0 (indicated by the red dashed line), which together explain approximately 58% of the total variance in the data. The first component (PC1: Environmental Action) is particularly strong, with an eigenvalue of 2.10, while components 2-4 have eigenvalues ranging from 1.16 to 1.34. The apparent "elbow" in the plot after the fourth component provides additional justification for retaining these four components. The green circles highlight these important components that were retained for further analysis, as they represent meaningful underlying dimensions in the data while effectively reducing dimensionality from the original ten variables.

Figure 2: Principal Component Analysis of Expert Traits – Digital components

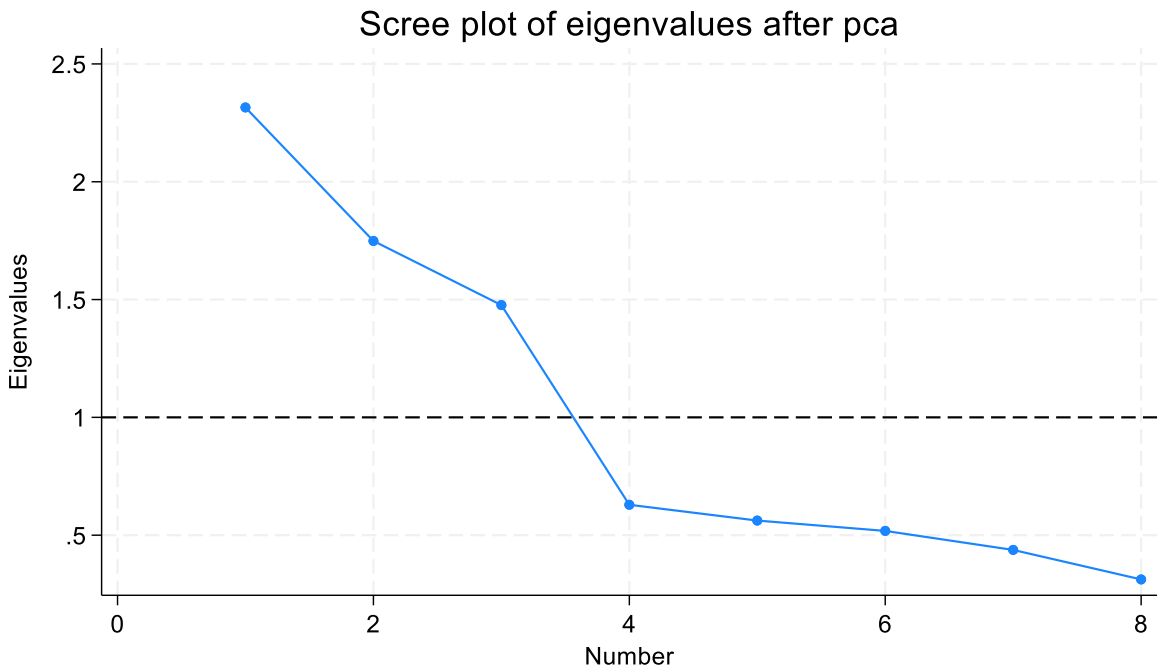


Note: A scree plot showing eigenvalues for each component with a reference line at eigenvalue = 1 (Kaiser Criterion), which demonstrates the proportion of variance explained by each component.

Personal components (Figure 3):

Prior to conducting PCA, we examined the correlation matrix to assess the appropriateness of factor analysis. The correlation analysis revealed several meaningful relationships, including a moderate correlation between general risk-taking and financial risk-taking (r = 0.61), as well as various correlations among the economic risk pricing variables (ranging from 0.32 to 0.59). These patterns suggested potential for dimensional reduction while preserving meaningful individual differences. We applied PCA with varimax rotation to enhance interpretability while maintaining statistical rigor. The Kaiser criterion (eigenvalues > 1.0) and scree plot analysis were used to determine the optimal number of components to retain. The initial unrotated solution identified three components with eigenvalues exceeding 1.0: Component 1 (eigenvalue = 2.32, accounting for 28.9% of the variance), Component 2 (eigenvalue = 1.75, accounting for 21.9% of the variance), and Component 3 (eigenvalue = 1.48, accounting for 18.5% of the variance). Together, these three components explained 69.3% of the total variance in the individual characteristics.

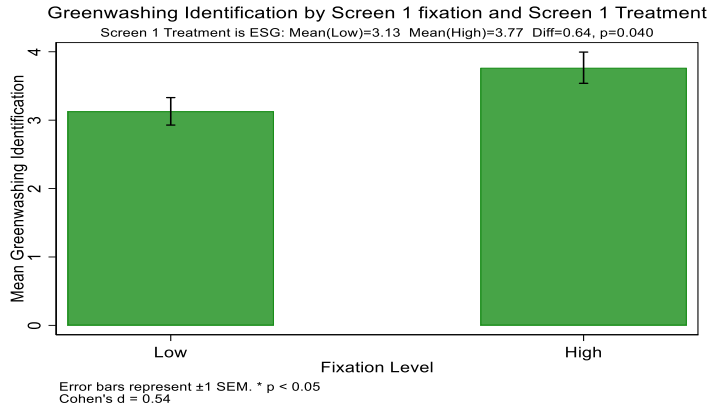
Figure 3: Principal Component Analysis of Expert Traits - Personal characteristics



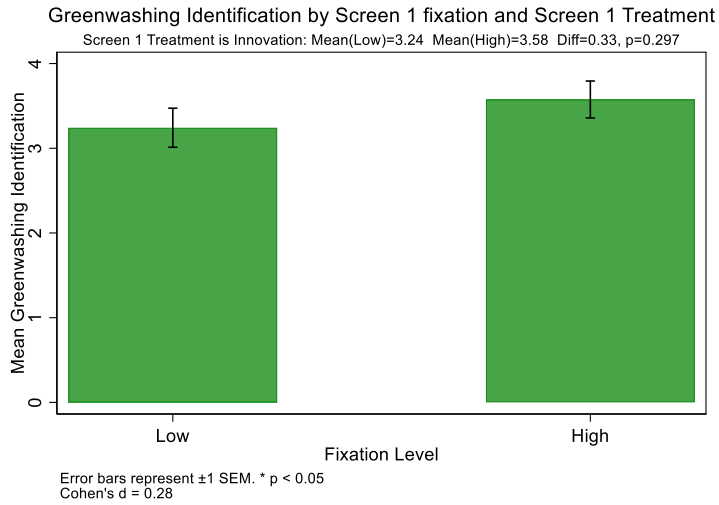
Appendix 3: RQ1 t- t-tests Visualization

Figures 1a-d: Attention Patterns in screen 1 and Washing Detection

Figures 1a-b: Higher Fixation on ESG content in screen1 significantly correlates with higher greenwashing identification

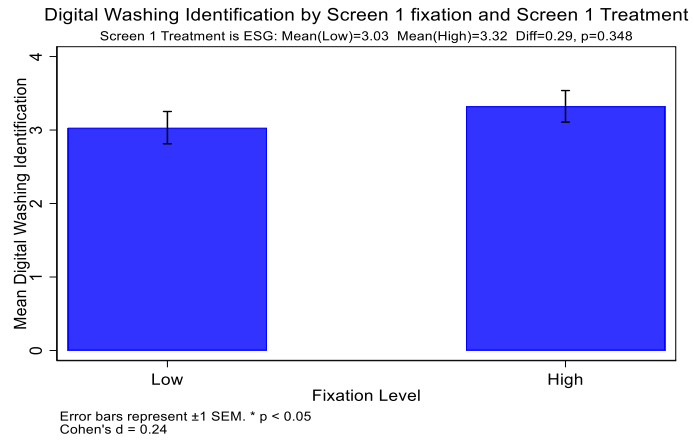


Note: Figure 1-a illustrates that participants with high fixation levels during the ESG treatment on Screen 1 have significantly higher greenwashing identification scores (M=3.77) compared to those with low fixation levels (M=3.13), with a difference of 0.64 (p=0.040, Cohen's d=0.54).



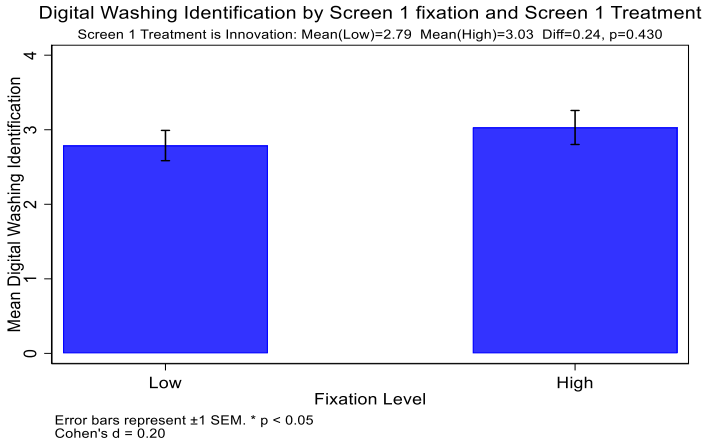
Note: Figure 1-b shows no significant difference in greenwashing identification scores between participants with high fixation levels (M=3.58) and those with low fixation levels (M=3.24) during Innovation treatment on Screen 1 (diff=0.33, p=0.297, Cohen's d=0.28).

Figures 1c-d: Higher Fixation on innovation (digital) content in screen 1 does not significantly correlate with higher digital washing identification



.

Note: Figure 1 -c shows no significant difference in digital washing identification scores between participants with high fixation levels (M=3.32) and those with low fixation levels (M=3.03) during ESG treatment on Screen 1 (diff=0.29, p=0.348, Cohen's d=0.24).



Note: Figure 1 -d shows no significant difference in digital washing identification scores between participants with high fixation levels (M=3.03) and those with low fixation levels (M=2.79) during Innovation treatment on Screen 1 (diff=0.24, p=0.430, Cohen's d=0.20).

Appendix 4A: RQ1 &RQ3 Fixation in Screen 3 Ambiguity – ESG Part

Absence of Trait Effects on Fixation Patterns in Screen 3 – ESG contradiction part

Table 1: ANOVA Results for ESG Trait Components and Contradiction Detection

Component	Sample	F-statistic	p-value	R^2	Adjusted R^2	Significant Comparisons
PC1: Environmental Action Orientation						
	Overall	0.23	0.797	0.004	-0.012	None
	ESG Version 1	0.10	0.909	0.003	-0.031	None
	ESG Version 0	0.39	0.680	0.012	-0.019	None
PC2: Media and Regulatory Influence						
	Overall	1.13	0.326	0.018	0.002	None
	ESG Version 1	0.08	0.925	0.003	-0.031	None
	ESG Version 0	0.74	0.481	0.023	-0.008	None
PC3: Governance and ESG Data Engagement						
	Overall	0.72	0.489	0.011	-0.004	None
	ESG Version 1	1.22	0.302	0.040	0.007	None
	ESG Version 0	0.13	0.880	0.004	-0.028	None

Note: N = 129 for overall sample, N = 62 for ESG Version 1, N = 66 for ESG Version 0. No pairwise comparisons reached statistical significance (all p > .05, Tukey-adjusted).

Table 2: Adjusted Predictions of ESG Contradiction Detection by Component Categories

Component	Category	Overall		ESG Version 1		ESG Version 0	
		Margin	SE	Margin	SE	Margin	SE
PC1: Environmental Action							
	Low	0.400***	0.100	0.400*	0.158	0.400**	0.131
	Medium	0.442***	0.070	0.357***	0.094	0.542***	0.104
	High	0.481***	0.070	0.417***	0.102	0.519***	0.098
PC2: Media Influence							
	Low	0.423***	0.098	0.417**	0.121	0.429**	0.139
	Medium	0.385***	0.069	0.364***	0.086	0.421**	0.121
	High	0.529***	0.070	0.412**	0.127	0.576***	0.094
PC3: Governance							
	Low	0.440***	0.100	0.333*	0.141	0.538***	0.142
	Medium	0.509***	0.069	0.500***	0.096	0.519***	0.098
	High	0.392***	0.070	0.292**	0.100	0.462***	0.100

Note: * p < .05, ** p < .01, *** p < .001. Significance levels refer to whether the individual category means differ from zero, not whether categories differ from each other.

Model Analysis

Table 3: Linear Regression Models Predicting ESG Contradiction Fixation Level

Variable	Model 1	Model 2	Model 3	Model 4
High relative fixation- screen1	0.009	0.011	0.028	0.030
	(0.022)	(0.025)	(0.030)	(0.031)
ESG Version	-0.012	0.037	0.084	0.089
	(0.023)	(0.067)	(0.095)	(0.096)
High fixation × ESG	0.025	0.029	0.027	0.028
	(0.032)	(0.037)	(0.045)	(0.045)
PC1 (Environmental Action)				
Medium		-0.008	-0.010	-0.010
		(0.031)	(0.036)	(0.037)
High		0.025	0.058	0.060
		(0.036)	(0.045)	(0.046)
PC1 × ESG				
Medium × ESG		-0.043	-0.073	-0.075
		(0.047)	(0.056)	(0.057)
High × ESG		-0.062	-0.119†	-0.121†
		(0.052)	(0.065)	(0.066)
PC2 (Media Influence)				
Medium		-0.002	-0.006	-0.007
		(0.034)	(0.039)	(0.040)
High		0.011	0.013	0.013
		(0.035)	(0.040)	(0.040)
PC2 × ESG				
Medium × ESG		-0.039	-0.052	-0.053
		(0.047)	(0.055)	(0.055)
High × ESG		-0.018	-0.048	-0.049
		(0.050)	(0.058)	(0.059)
PC3 (Governance)				
Medium		-0.048	-0.036	-0.037
		(0.035)	(0.040)	(0.040)
High		-0.066†	-0.058	-0.060
		(0.038)	(0.042)	(0.043)
PC3 × ESG				
Medium × ESG		0.058	0.052	0.054
		(0.049)	(0.054)	(0.055)
High × ESG		0.023	-0.006	-0.006
		(0.052)	(0.059)	(0.060)
PC4 (Climate Risk)				
Medium		0.024	0.015	0.016
		(0.033)	(0.042)	(0.042)
High		-0.014	-0.012	-0.012
		(0.040)	(0.049)	(0.050)
PC4 × ESG				
Medium × ESG		-0.029	0.014	0.015
		(0.047)	(0.059)	(0.060)
High × ESG		0.003	0.052	0.053
		(0.056)	(0.070)	(0.071)
Demographic Category				
Medium			0.042	0.043
			(0.036)	(0.036)
High			0.085*	0.087*
			(0.037)	(0.037)
Demographic × ESG				
Medium × ESG			0.022	0.022
			(0.052)	(0.052)
High × ESG			0.004	0.004
			(0.051)	(0.052)
Risk Taking Category				

Medium			0.068†	0.069†
			(0.037)	(0.038)
High			0.046	0.047
			(0.032)	(0.032)
Risk Taking × ESG				
Medium × ESG			-0.031	-0.031
			(0.050)	(0.051)
High × ESG			0.013	0.013
			(0.047)	(0.047)
Perception Risks Category				
High			0.024	0.024
			(0.028)	(0.029)
Very High			-0.020	-0.020
			(0.071)	(0.071)
Perception Risks × ESG				
High × ESG			-0.015	-0.016
			(0.043)	(0.044)
Very High × ESG			0.008	0.009
			(0.107)	(0.108)
Gender				0.004
				(0.022)
Gender × ESG				-0.005
				(0.031)
Constant	0.216***	0.244***	0.168*	0.166*
	(0.016)	(0.043)	(0.073)	(0.074)
Model Statistics				
Observations	128	128	112	112
F-statistic	0.80	0.77	1.05	1.01
Prob > F	0.496	0.741	0.417	0.473
R^2	0.019	0.119	0.289	0.290
Adjusted R^2	-0.005	-0.036	0.014	0.003

Note: Standard errors in parentheses. Model 1 includes only high relative fixation, ESG version, and their interaction. Model 2 adds all ESG trait components and their interactions with ESG version. Model 3 adds personal characteristics and their interactions with ESG version. Model 4 adds gender and their interactions with ESG version. Reference categories are Low for all trait components and No for ESG Version. † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 4: Logistic Regression Models Predicting High ESG Contradiction Detection

Variable	Model 1	Model 2	Model 3	Model 4
High relative fixation- screen1	0.611	0.765	1.933*	2.042*
	(0.498)	(0.591)	(0.865)	(0.889)
	[1.843]	[2.149]	[6.909]	[7.705]
ESG Version	-0.588	-1.076	0.784	0.902
	(0.530)	(1.629)	(2.695)	(2.743)
	[0.555]	[0.341]	[2.190]	[2.464]
High fixation × ESG	0.219	0.285	-0.710	-0.798
	(0.731)	(0.905)	(1.290)	(1.312)
	[1.244]	[1.329]	[0.492]	[0.450]
PC1 (Environmental Action)				
Medium		0.937	1.653†	1.701†
		(0.753)	(0.974)	(0.986)
		[2.552]	[5.221]	[5.479]
High		1.179	2.708*	2.813*
		(0.853)	(1.297)	(1.315)
		[3.252]	[14.996]	[16.662]
PC1 × ESG				
Medium × ESG		-1.159	-2.191	-2.243
		(1.134)	(1.592)	(1.614)
		[0.314]	[0.112]	[0.106]
High × ESG		-0.991	-2.436	-2.501
		(1.227)	(1.836)	(1.859)
		[0.371]	[0.087]	[0.082]

PC2 (Media Influence)				
Medium		0.048	-0.091	-0.103
		(0.779)	(0.967)	(0.982)
		[1.049]	[0.913]	[0.902]
High		1.174	1.485	1.523
		(0.846)	(1.086)	(1.101)
		[3.236]	[4.417]	[4.586]
PC2 × ESG				
Medium × ESG		-0.752	-0.792	-0.813
		(1.117)	(1.424)	(1.443)
		[0.471]	[0.453]	[0.444]
High × ESG		-1.388	-1.476	-1.512
		(1.214)	(1.585)	(1.607)
		[0.250]	[0.229]	[0.220]
PC3 (Governance)				
Medium		-0.813	-1.138	-1.165
		(0.855)	(1.030)	(1.045)
		[0.443]	[0.321]	[0.312]
High		-1.077	-0.545	-0.559
		(0.919)	(1.074)	(1.089)
		[0.341]	[0.580]	[0.572]
PC3 × ESG				
Medium × ESG		1.561	1.558	1.596
		(1.191)	(1.409)	(1.429)
		[4.764]	[4.749]	[4.932]
High × ESG		0.507	-0.436	-0.447
		(1.303)	(1.645)	(1.668)
		[1.660]	[0.646]	[0.640]
PC4 (Climate Risk)				
Medium		-0.415	0.066	0.068
		(0.751)	(1.031)	(1.046)
		[0.660]	[1.069]	[1.070]
High		-0.812	-1.078	-1.104
		(0.938)	(1.216)	(1.233)
		[0.444]	[0.340]	[0.332]
PC4 × ESG				
Medium × ESG		1.770	1.787	1.831
		(1.194)	(1.587)	(1.609)
		[5.873]	[5.970]	[6.239]
High × ESG		1.739	2.896	2.967
		(1.405)	(1.878)	(1.904)
		[5.693]	[18.097]	[19.434]
Demographic Category				
Medium			0.087	0.089
			(0.886)	(0.898)
			[1.091]	[1.093]
High			0.792	0.811
			(1.070)	(1.084)
			[2.207]	[2.250]
Demographic × ESG				
Medium × ESG			-0.552	-0.566
			(1.411)	(1.430)
			[0.576]	[0.568]
High × ESG			0.322	0.330
			(1.440)	(1.460)
			[1.380]	[1.391]
Risk Taking Category				
Medium			0.572	0.586
			(0.987)	(1.000)
			[1.772]	[1.797]
High			0.709	0.726
			(0.856)	(0.868)
			[2.033]	[2.067]

Risk Taking × ESG				
Medium × ESG			1.105	1.132
			(1.431)	(1.451)
			[3.019]	[3.102]
High × ESG			0.746	0.765
			(1.278)	(1.296)
			[2.110]	[2.149]
Perception Risks Category				
High			0.977	1.001
			(0.772)	(0.783)
			[2.657]	[2.721]
Perception Risks × ESG				
High × ESG			-2.285†	-2.341†
			(1.173)	(1.189)
			[0.102]	[0.096]
Gender				0.243
				(0.627)
				[1.275]
Gender × ESG				-0.187
				(0.893)
				[0.829]
Constant	-0.305	-0.549	-3.227	-3.349
	(0.352)	(0.992)	(2.001)	(2.042)
	[0.737]	[0.577]	[0.040]	[0.035]
Model Statistics				
Observations	128	128	108	108
LR Chi^2	5.64	18.95	32.91	33.18
Prob > Chi^2	0.130	0.460	0.281	0.318
Pseudo R^2	0.032	0.108	0.221	0.223

Note: Coefficients are presented with standard errors in parentheses and odds ratios in brackets. . Model 1 includes only high relative fixation, ESG version, and their interaction. Model 2 adds all ESG trait components and their interactions with ESG version. Model 3 adds personal characteristics and their interactions with ESG version. Model 4 adds gender and their interactions with ESG version. Reference categories are Low for all trait components and No for ESG Version. † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Appendix 4B: RQ1 &RQ3 Fixation in Screen 3 Ambiguity – Innovation Part

Absence of Trait Effects on Fixation Patterns – Innovation

Table 1: ANOVA Results for Digital Components and Innovation Contradiction Detection

Component	Sample	F-statistic	p-value	R^2	Adjusted R^2	Significant Comparisons
PC1: Digital-Technological Tendency						
	Overall	0.83	0.439	0.013	-0.003	None
	ESG Version 1	0.42	0.661	0.014	-0.020	None
	ESG Version 0	0.37	0.693	0.012	-0.020	None
PC2: Digital-Cyber and Innovation Identification						
	Overall	2.81	0.064†	0.043	0.028	Medium vs Low (p=0.059†)
	ESG Version 1	0.98	0.381	0.032	-0.001	None
	ESG Version 0	2.01	0.143	0.060	0.030	None
PC3: Digital-Operational Risk Importance						
	Overall	1.83	0.165	0.028	0.013	None
	ESG Version 1	0.08	0.925	0.003	-0.031	None
	ESG Version 0	0.74	0.481	0.023	-0.008	None

Note: N = 128 for overall sample, N = 62 for ESG Version 1, N = 66 for ESG Version 0. † p < 0.10 indicates marginal significance.

Table 2: Adjusted Predictions of Innovation Contradiction Detection by Digital Component Categories

Component	Category	Overall		ESG Version 1		ESG Version 0	
		Margin	SE	Margin	SE	Margin	SE
PC1: Digital-Technological Tendency							
	Low	0.520***	0.100	0.583***	0.144	0.462**	0.141
	Medium	0.519***	0.069	0.538***	0.098	0.500***	0.100
	High	0.635***	0.069	0.667***	0.102	0.593***	0.098
PC2: Digital-Cyber and Innovation Identification							
	Low	0.360***	0.098	0.417**	0.121	0.286*	0.139
	Medium	0.635***	0.068	0.583***	0.086	0.684***	0.105
	High	0.596***	0.068	0.500***	0.102	0.667***	0.094
PC3: Digital-Operational Risk Importance							

	Low	0.480***	0.098	0.417**	0.121	0.538***	0.142
	Medium	0.596***	0.068	0.417***	0.086	0.737***	0.098
	High	0.462***	0.068	0.417***	0.102	0.500***	0.094

Note: * p < .05, ** p < .01, *** p < .001. Significance levels refer to whether the individual category means differ from zero, not whether categories differ from each other.

Table 3: Linear Regression Analysis Models Predicting Attention to Innovation Contradiction (Fixation)

Linear regression models predicting continuous contradiction detection showed consistently weak explanatory power across increasingly complex models: digital components (Model 2: $F(15, 112) = 0.51$, $p = .932$, $R^2 = .064$), individual characteristics (Model 3: $F(27, 84) = 0.55$, $p = .958$, $R^2 = .151$), and gender (Model 4: $F(29, 81) = 0.59$, $p = .945$, $R^2 = .174$). Coefficients for fixation type, ESG version, and interactions remained small and non-significant. One marginal trend emerged for the interaction between high Digital-Technological Tendency (PC1) and ESG version ($\beta = -0.0705$, $SE = 0.0405$), though this weakened in later models.

Variable	Model 1	Model 2	Model 3	Model 4
High relative fixation- screen1	0.008	0.009	-0.001	-0.001
	(0.017)	(0.019)	(0.022)	(0.022)
ESG Version	0.000	0.026	0.010	0.006
	(0.018)	(0.048)	(0.074)	(0.077)
High fixation × ESG	-0.014	-0.007	-0.007	-0.009
	(0.025)	(0.028)	(0.033)	(0.034)
PC1 (Digital-Technological)				
Medium		0.001	0.003	0.004
		(0.026)	(0.028)	(0.028)
High		0.020	0.001	0.006
		(0.027)	(0.031)	(0.032)
PC1 × ESG				
Medium × ESG		-0.036	-0.031	-0.032
		(0.038)	(0.043)	(0.043)
High × ESG		-0.071†	-0.037	-0.041
		(0.041)	(0.047)	(0.048)
PC2 (Digital-Cyber)				
Medium		0.017	0.008	0.006
		(0.025)	(0.030)	(0.030)
High		-0.002	-0.005	0.003
		(0.026)	(0.032)	(0.033)
PC2 × ESG				

Medium × ESG		-0.002	-0.002	-0.002
		(0.037)	(0.043)	(0.043)
High × ESG		-0.015	-0.008	-0.018
		(0.038)	(0.048)	(0.049)
PC3 (Digital-Operational)				
Medium		0.017	0.023	0.025
		(0.026)	(0.029)	(0.029)
High		0.003	0.020	0.025
		(0.026)	(0.030)	(0.030)
PC3 × ESG				
Medium × ESG		-0.002	0.001	-0.000
		(0.037)	(0.042)	(0.043)
High × ESG		0.059	0.027	0.023
		(0.045)	(0.056)	(0.056)
Demographic Category				
Medium			0.005	0.019
			(0.026)	(0.028)
High			-0.050	-0.036
			(0.031)	(0.032)
Demographic × ESG				
Medium × ESG			-0.034	-0.047
			(0.040)	(0.041)
High × ESG			0.023	0.012
			(0.041)	(0.043)
Risk Taking Category				
Medium			0.017	0.020
			(0.028)	(0.028)
High			0.013	0.014
			(0.027)	(0.027)
Risk Taking × ESG				
Medium × ESG			-0.018	-0.022
			(0.039)	(0.039)
High × ESG			-0.022	-0.024
			(0.038)	(0.038)
Perception Risks Category				

High			-0.009	-0.022
			(0.022)	(0.024)
Very High			0.008	-0.007
			(0.056)	(0.057)
Perception Risks × ESG				
High × ESG			0.039	0.052
			(0.032)	(0.033)
Very High × ESG			0.039	0.057
			(0.081)	(0.083)
Gender (Male)				-0.036
				(0.024)
Gender × ESG				0.029
				(0.033)
Constant	0.194***	0.172***	0.186***	0.196***
	(0.012)	(0.033)	(0.052)	(0.054)
Model Statistics				
Observations	128	128	112	111
F-statistic	0.20	0.51	0.55	0.59
Prob > F	0.898	0.932	0.958	0.945
R^2	0.005	0.064	0.151	0.174
Adjusted R^2	-0.019	-0.062	-0.122	-0.122
Root MSE	0.070	0.071	0.073	0.073

Note: Table presents unstandardized coefficients with standard errors in parentheses. Model 1 includes only high relative fixation in screen 1, ESG ***version, and their interaction. Model 2 adds digital component categories (PC1-PC3) and their interactions with ESG version. Model 3 incorporates personal characteristics (demographic, risk-taking, perception risks) and their interactions. Model 4 includes gender and its interaction with ESG version. Reference categories are: Low (for PC1, PC2, PC3, demographic, risk-taking, and perception risks categories) and Female (for gender). † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001***

Logistic regression models mirrored linear results but revealed noteworthy effects. Base model was non-significant ($\chi^2(3) = 1.24$, $p = .744$, Pseudo $R^2 = .007$), and expanded models remained non-significant overall despite improved fit. However, medium Digital-Cyber and Innovation Identification (PC2) emerged as significant predictor from Model 2 onward (Model 4: $\beta = 2.086$, $SE = 1.064$, $p < .05$), suggesting participants with medium PC2 scores were over seven times more likely to detect innovation contradictions compared to low category (Table 4).

High perceived risk showed significant negative effects ($\beta = -2.028$, $SE = 0.844$, $p < .05$), indicating that those perceiving high risk were less likely to detect contradictions. Conversely, the interaction between high risk perception and ESG version was significantly positive ($\beta = 2.745$, $SE = 1.136$, $p < .05$), suggesting complex interaction effects. Gender showed substantial interaction with ESG version ($\beta = 2.540$, $SE = 1.127$, $p < .05$), indicating male participants in ESG conditions were more likely to identify contradictions. **These**

patterns highlight important intersections between digital awareness components, perceived risk, and experimental context.

Table 4: Logistic Regression Models Predicting Attention to Innovation Contradiction (Fixation)

Variable	Model 1	Model 2	Model 3	Model 4
High relative fixation- screen1	0.122	0.248	0.542	0.581
	(0.494)	(0.564)	(0.696)	(0.713)
ESG Version	0.537	0.095	0.519	-0.501
	(0.512)	(1.461)	(2.293)	(2.484)
High fixation × ESG	-0.525	-0.359	-0.242	0.281
	(0.717)	(0.829)	(1.066)	(1.156)
PC1 (Digital-Technological)				
Medium		-0.192	-0.630	-0.829
		(0.767)	(0.879)	(0.925)
High		0.649	0.382	0.392
		(0.795)	(0.981)	(1.019)
PC1 × ESG				
Medium × ESG		-0.072	-1.020	-1.232
		(1.139)	(1.385)	(1.525)
High × ESG		-1.058	-1.711	-2.193
		(1.234)	(1.556)	(1.662)
PC2 (Digital-Cyber)				
Medium		1.638*	2.011*	2.086*
		(0.773)	(1.006)	(1.064)
High		0.702	1.088	1.474
		(0.772)	(1.032)	(1.117)
PC2 × ESG				
Medium × ESG		-0.464	-0.549	-0.411
		(1.143)	(1.453)	(1.513)
High × ESG		-0.169	-0.107	0.077
		(1.129)	(1.511)	(1.645)
PC3 (Digital-Operational)				
Medium		-0.366	0.063	0.391
		(0.769)	(0.866)	(0.902)
High		-0.004	0.491	0.826
		(0.756)	(0.892)	(0.943)

PC3 × ESG				
Medium × ESG		1.159	0.420	-0.070
		(1.077)	(1.267)	(1.305)
High × ESG		1.875	1.125	0.823
		(1.382)	(1.753)	(1.757)
Demographic Category				
Medium			1.043	1.765†
			(0.790)	(0.920)
High			0.467	0.967
			(0.937)	(0.996)
Demographic × ESG				
Medium × ESG			-0.271	-1.059
			(1.267)	(1.373)
High × ESG			-0.894	-1.884
			(1.258)	(1.349)
Risk Taking Category				
Medium			0.420	0.462
			(0.859)	(0.907)
High			-0.416	-0.364
			(0.821)	(0.889)
Risk Taking × ESG				
Medium × ESG			-0.437	-0.369
			(1.217)	(1.270)
High × ESG			1.461	1.562
			(1.187)	(1.262)
Perception Risks Category				
High			-1.416*	-2.028*
			(0.714)	(0.844)
Very High			(empty)	(empty)
			-	-
Perception Risks × ESG				
High × ESG			2.049*	2.745*
			(1.019)	(1.136)
Very High × ESG			(omitted)	(omitted)
			-	-

Gender (Male)				-1.153
				(0.797)
Gender × ESG				2.540*
				(1.127)
Constant	0.061	-1.009	-1.428	-1.428
	(0.348)	(0.995)	(1.646)	(1.646)
Model Statistics				
Observations	128	128	112	111
Pseudo R^2	0.014	0.091	0.259	0.274
LR Chi^2	2.17	14.58	35.98	37.46
Prob > Chi^2	0.537	0.482	0.072†	0.087†
Log likelihood	-79.183	-72.981	-51.424	-49.604

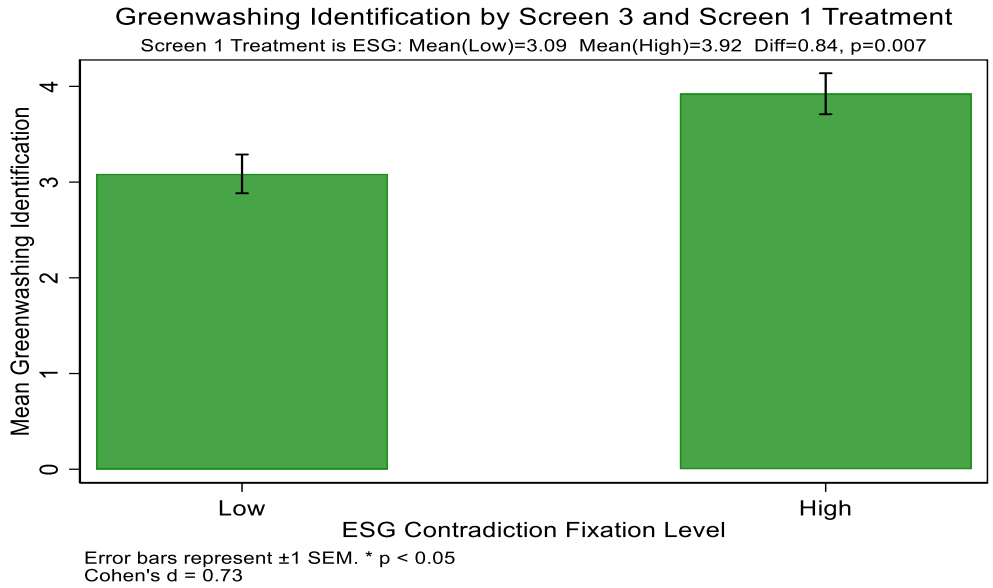
Note: Table presents logistic regression coefficients with standard errors in parentheses. Model 1 includes only high relative fixation in screen 1, ESG version, and their interaction. Model 2 adds digital component categories (PC1-PC3) and their interactions with ESG version. Model 3 incorporates personal characteristics (demographic, risk-taking, perception risks) and their interactions. Model 4 includes gender and its interaction with ESG version. Reference categories are: Low (for PC1, PC2, PC3, demographic, risk-taking, and perception risks categories) and Female (for gender). † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.0

Appendix 5: Attention Effects on Washing Identification

Contradiction-Specific Attention Effects (RQ1)

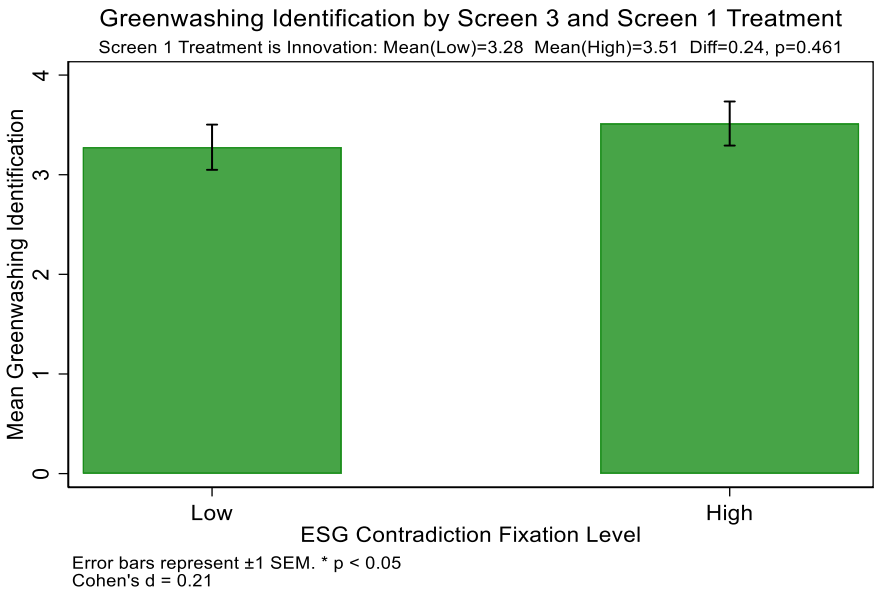
The relationship between attention and potential washing identification strengthened during contradiction identification (Screen 3). ESG treatment participants with higher fixation on ambiguous ESG content showed substantially higher potential greenwashing identification (M = 3.92 vs. M = 3.09; t(60) = 2.78, p = 0.007, Cohen's d = 0.73). This significant effect aligns with dual-process theories (Kahneman, 2011), suggesting that attention to contradictory information enhances the systematic processing of potential deception cues and plays a crucial role in identifying potential "washing" by experts. Conversely, Innovation treatment showed no significant Screen 3 attention differences, with potential digital washing identification unrelated to Innovation contradiction fixation across conditions (all p > 0.38). This pattern suggests fundamental differences in how financial experts process environmental versus technological claims, potentially reflecting varying domain expertise or established evaluation frameworks.

Figure 1 : Greenwashing identification by high and low fixation levels in ESG Ambiguity in screen 3 by Screen 1 treatment ESG



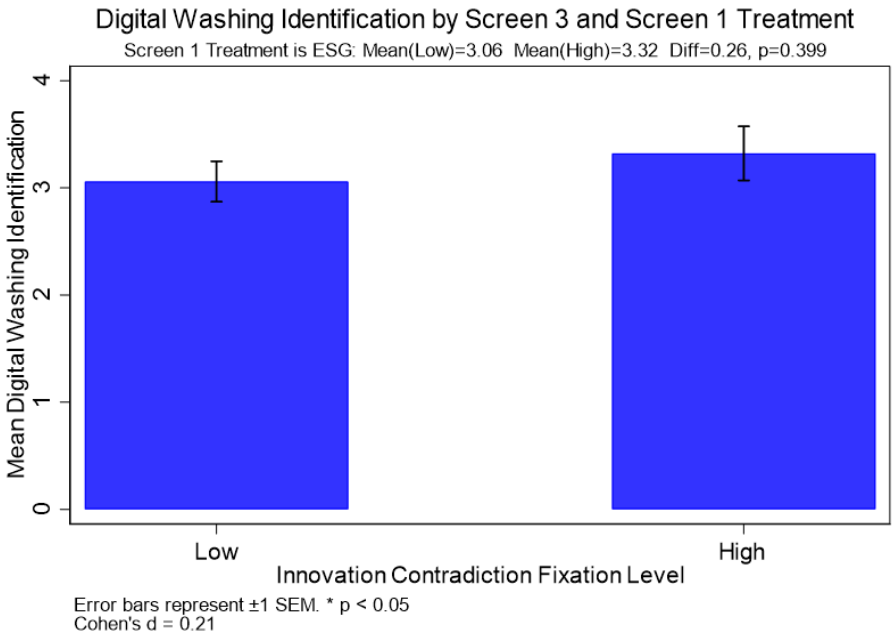
Note: Figure 1 shows significantly higher greenwashing identification scores for participants with high ESG contradiction fixation levels (M=3.92) compared to those with low fixation levels (M=3.09) during ESG treatment on Screen 1 (diff=0.84, p=0.007, Cohen's d=0.73).

Figure 2 : Greenwashing identification by high and low fixation levels in ESG Ambiguity in screen 3 by Screen 1 treatment Innovation



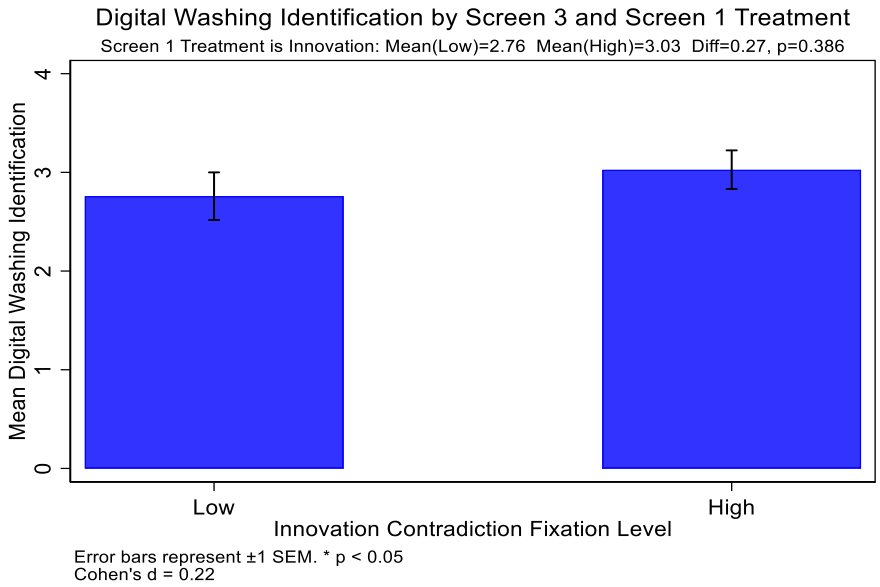
Note: Figure 2 shows no significant difference in greenwashing identification scores between participants with high ESG contradiction fixation levels (M=3.51) and those with low fixation levels (M=3.28) during Innovation treatment on Screen 1 (diff=0.24, p=0.461, Cohen's d=0.21).

Figures 3 : Digital - Washing identification by high and low Fixation levels in Innovation ambiguity in screen 3 by Screen 1 treatment ESG



Note: Figure 3 shows no significant difference in digital washing identification scores between participants with high innovation contradiction fixation levels (M=3.32) and those with low fixation levels (M=3.06) during ESG treatment on Screen 1 (diff=0.26, p=0.399, Cohen's d=0.21).

Figure 4: Digital - Washing identification by high and low Fixation levels in Innovation ambiguity in screen 3 by Screen 1 treatment Innovation



Note: Figure 4 shows no significant difference in digital washing identification scores between participants with high innovation contradiction fixation levels (M=3.03) and those with low fixation levels (M=2.76) during Innovation treatment on Screen 1 (diff=0.27, p=0.386, Cohen's d=0.22).

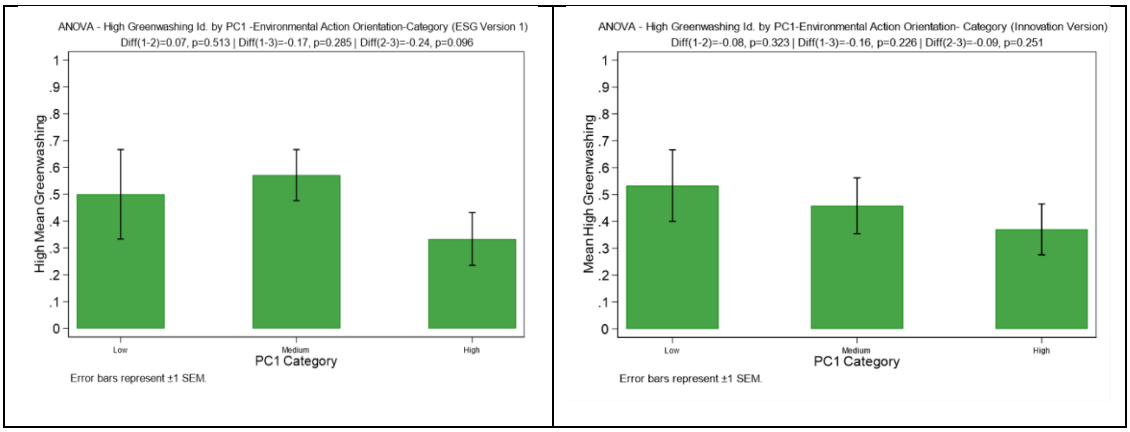
Appendix 5A: Trait Effects on Greenwashing Identification - Detailed Analysis (RQ1&RQ4)

Trait Effects on Potential Washing Identification

T-test analyses revealed complex patterns of individual traits' influence on potential greenwashing detection in corporate communications.

Environmental Action Orientation showed contrasting patterns across conditions. In an ESG context, participants with a high environmental orientation demonstrated lower potential greenwashing identification compared to those with a medium orientation (M_medium = 0.57 vs. M_high = 0.33; diff = -0.24, p = 0.096), suggesting a paradoxical effect where stronger environmental values may hinder critical assessment of potential greenwashing claims. In the Innovation condition, potential greenwashing identification decreased linearly as Environmental Action Orientation increased, though differences were non-significant (all p > 0.20). This contrast suggests framing effects moderate how personal environmental values influence potential greenwashing detection (Figures 1a and 1b).

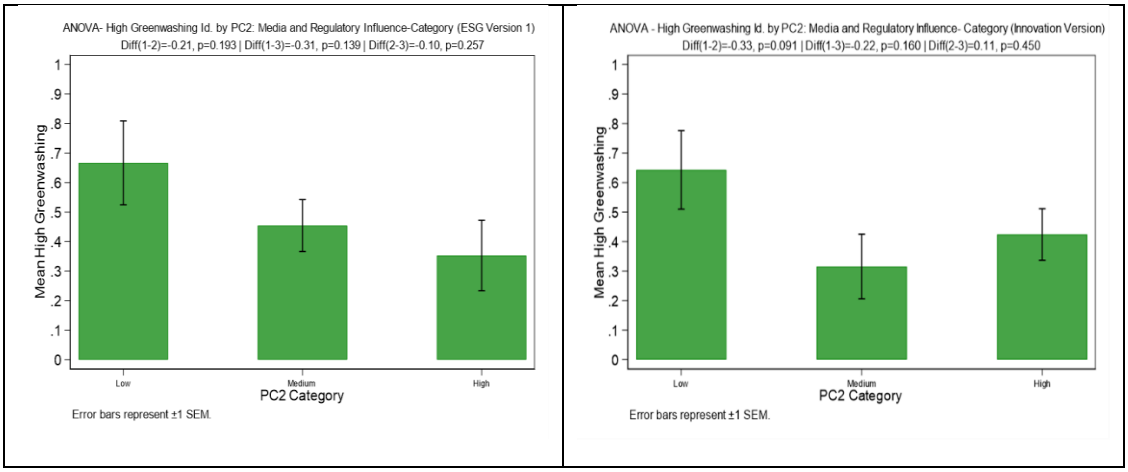
Figures 1 a-b : Environmental Action Orientation (PC1) and Greenwashing Identification



Note: Figures 1 a and 9 b Bar charts depicting the relationship between Environmental Action Orientation (PC1) and Greenwashing Identification across experimental conditions. The left panel shows results for the ESG Version condition, revealing an inverted U-shaped pattern where participants with medium Environmental Action Orientation demonstrated the highest greenwashing identification (M≈0.57), significantly higher than those with high orientation (M≈0.33; Diff(2-3)=-0.24, p=0.096). The right panel displays the results for the Innovation Version condition, showing a more linear negative relationship between Environmental Action Orientation and greenwashing identification, although the differences were not statistically significant. Error bars represent ±1 SEM. This figure illustrates the paradoxical effect where stronger environmental values may inhibit the critical assessment of greenwashing claims, particularly when individuals are primed with ESG-related content.

Media and Regulatory Influence awareness demonstrated a consistent negative association with potential greenwashing identification across conditions. In the ESG condition, participants with low media awareness showed the highest potential for greenwashing identification (M = 0.67), followed by a progressive decrease in medium (M = 0.45) and high (M = 0.36) awareness groups (diff_low-high = -0.31, p = 0.139). Similar patterns emerged in the Innovation condition, with low awareness showing substantially higher identification (M = 0.65) compared to medium (M = 0.32) and high (M = 0.42) awareness groups (diff_low-medium = -0.33, p = 0.091). This inverse relationship suggests a skepticism paradox, wherein individuals less attuned to media influences adopt more critical stances toward corporate environmental claims (Figures 1c and 1d).

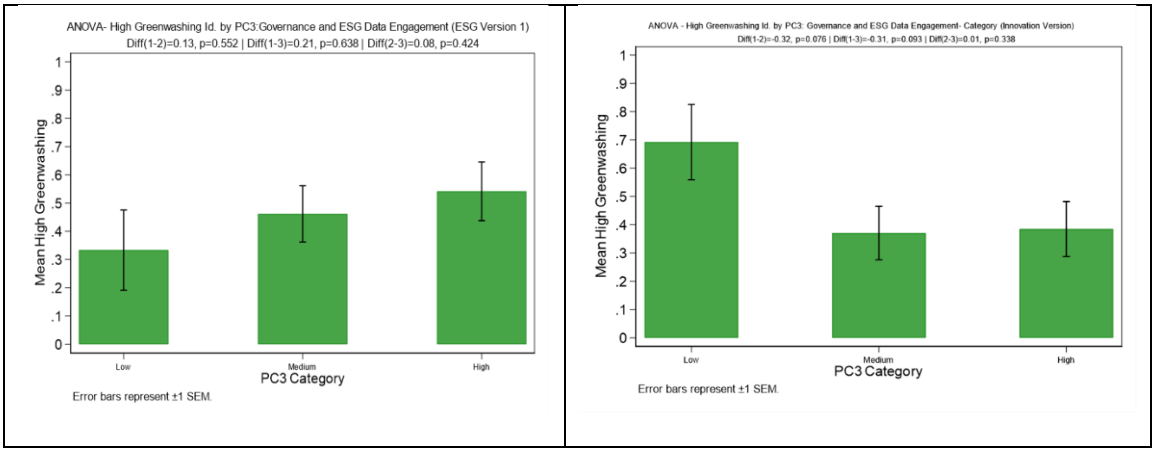
Figures 1 c -d: Media and Regulatory Influence (PC2) and Greenwashing Identification



Note: Figures 9 c and 9 d: Bar charts depicting the consistent negative relationship between Media and Regulatory Influence awareness (PC2) and Greenwashing Identification across experimental conditions. In both the ESG Version (left panel) and Innovation Version (right panel) conditions, participants with low Media and Regulatory Influence awareness demonstrated the highest greenwashing identification (M≈0.67 and M≈0.65, respectively), with lower identification observed in medium and high awareness groups. The difference between low and medium groups in the Innovation condition approached significance (Diff(1-2)=-0.33, p=0.091). Error bars represent ±1 SEM. This figure illustrates the skepticism paradox, wherein individuals less aware of media and regulatory influences on ESG reporting may be more critical in their evaluation of corporate environmental claims, perhaps due to general distrust rather than informed assessment.

Governance and ESG Data Engagement revealed contrasting patterns across conditions. In ESG condition, a positive linear trend emerged with potential greenwashing identification increasing from low (M = 0.33) to medium (M = 0.46) to high (M = 0.54) engagement levels (diff_low-high = 0.21, p = 0.638). However, in the Innovation condition, an inverse pattern was observed, with low-engagement participants showing markedly higher potential for greenwashing identification (M = 0.70) compared to medium (M = 0.37) and high (M = 0.38) engagement groups (diff_low-medium = -0.32, p = 0.093). This interaction effect indicates that governance awareness influences potential greenwashing detection differently depending on the initial framing context (Figures 1e and 1f).

Figures 1 e-f : Governance and ESG Data Engagement (PC3) and Greenwashing Identification

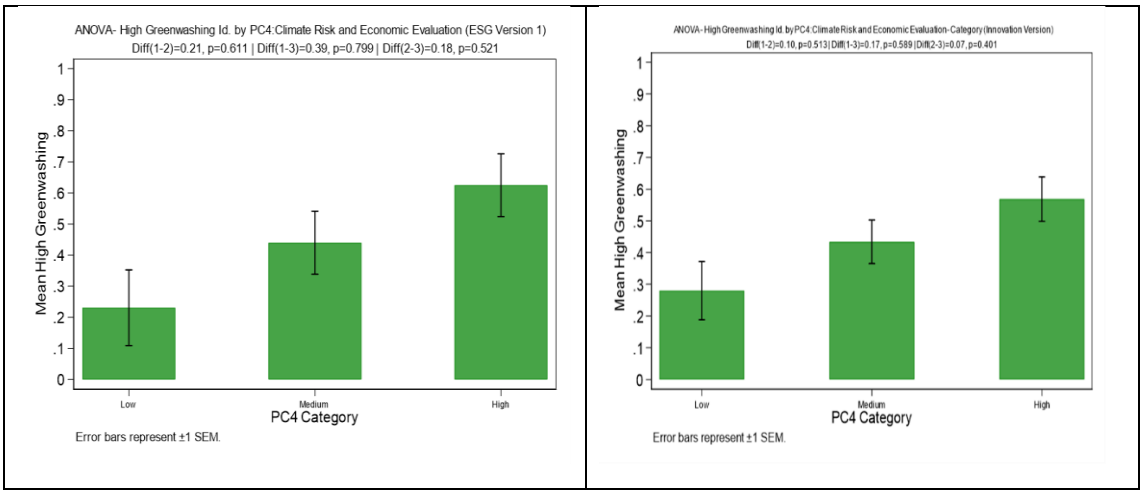


Note: Figures 9e and 9f: Bar charts showing the contrasting relationship between Governance and ESG Data Engagement (PC3) and Greenwashing Identification across experimental conditions. The ESG Version condition (left panel) displays a positive linear trend with greenwashing identification increasing from low (M≈0.33) to medium (M≈0.46) to high (M≈0.54) levels of engagement. In stark contrast, the Innovation Version condition (right panel) shows an inverse pattern, with participants demonstrating low engagement exhibiting markedly higher greenwashing identification (M≈0.70) compared to both medium (M≈0.37) and high (M≈0.38) engagement groups. Error bars represent ±1 SEM. This figure

highlights how the influence of governance awareness on greenwashing detection is moderated by the initial framing context, with opposite patterns emerging depending on whether participants were primed with ESG or innovation-related content.

Climate Risk and Economic Evaluation demonstrated consistent positive linear trends across both conditions. In the ESG condition, participants with high climate risk awareness showed notably higher greenwashing identification (M = 0.62) compared to those with low awareness (M = 0.21; diff_low-high = 0.39, p = 0.799). Similarly, in Innovation conditions, identification increased with higher climate risk awareness (Low: M = 0.29; High: M = 0.57; diff_low-high = 0.17, p = 0.58). This consistent pattern suggests that individuals who recognize the economic implications of climate risks are more attuned to detecting greenwashing claims, regardless of the framing context. However, the results are not statistically significant in the current sample size (Figures 1g and 1h).

Figures 1 g-h: Climate Risk and Economic Evaluation (PC4) and Greenwashing Identification



Note: Figures 9g and 9h: Bar charts illustrate the relationship between Climate Risk and Economic Evaluation (PC4) and Greenwashing Identification across experimental conditions. Both panels demonstrate a positive linear trend, where greenwashing identification increases with higher levels of awareness of Climate Risk and Economic Evaluation. In the ESG Version condition (left panel), participants with high awareness showed notably higher greenwashing identification (M≈= 0.62) compared to those with low awareness (M≈= 0.23). Similarly, in the Innovation Version condition (right panel), greenwashing identification increased from low (M≈0.29) to medium (M≈0.45) to high (M≈0.57) levels of awareness, with the difference between low and high groups approaching significance (Diff(1-3)=0.17, p=0.589). Error bars represent ±1 SEM. This figure demonstrates that, unlike other components, greater awareness of climate-related economic impacts consistently enhances the critical evaluation of corporate environmental claims, regardless of the framing context.

To validate our t-test findings and examine more complex relationships, we conducted comprehensive regression analyses as robustness checks for our main results. The multiple regression analysis revealed several important findings regarding predictors of greenwashing identification.

Model 1, which focused solely on ESG contradictions, demonstrated a significant positive relationship (β = 2.162, p < 0.05), confirming that greater attention to contradictory information enhances the detection of greenwashing. This relationship persisted in the expanded Model 2 (β = 2.276, p < 0.10), though with slightly reduced significance when controlling for personality components and experimental conditions.

Among ESG-related traits components, Media and Regulatory Influence (PC2) emerged as a component with significant direct effects. Participants with medium (β = -0.858, p < 0.10) and high (β = -1.085, p < 0.05) media awareness demonstrated significantly lower greenwashing identification compared to participants with low awareness, confirming our t-test findings of a skepticism paradox wherein individuals more aware of media and regulatory dynamics may be less likely to identify specific instances of

greenwashing, perhaps due to generalized skepticism toward ESG claims or higher thresholds for what constitutes greenwashing.

Governance and ESG Data Engagement (PC3) exhibits complex, context-dependent relationships with greenwashing identification. In linear regression, the relationship was not statistically significant. However, in logistic regression, high Governance engagement showed a significant adverse main effect (coefficient = -4.057, $p < 0.05$ in Model 3). However, this was strongly moderated by ESG version, with a significant positive interaction effect (coefficient = 7.617, $p < 0.01$ in Model 3). This suggests that governance awareness influences the detection of greenwashing differently depending on contextual framing. In the Innovation version condition, high governance engagement was associated with lower greenwashing identification, while in the ESG version condition, the relationship was positive.

Climate Risk and Economic Evaluation (PC4) revealed positive relationships, particularly for high-category participants ($\beta = 0.965$, $p = 0.124$), although this did not reach conventional significance. The overall model explained approximately 24% of the variance in greenwashing identification ($R^2 = 0.237$, adjusted $R^2 = 0.059$). Logistic regression analysis provided additional insights into factors predicting high greenwashing identification as a binary outcome. A high fixation on ESG contradictions significantly increased the odds of high greenwashing identification (OR = 4.09, $p < 0.05$), reinforcing the importance of attention allocation. Media and Regulatory Influence (PC2) again showed strong adverse effects, with medium (OR = 0.02, $p < 0.05$) and high (OR = 0.01, $p < 0.05$) awareness categories substantially reducing odds of high identification. Conversely, Climate Risk and Economic Evaluation (PC4) demonstrated powerful positive effects, with medium (OR = 48.37, $p < 0.05$) and high (OR = 164.86, $p < 0.05$) awareness categories significantly increasing the odds of identification. The logistic regression revealed significant interaction effects not apparent in linear models and T- tests, including interactions between Governance and ESG Data Engagement (PC3) and ESG Version (OR = 84.74, $p < 0.05$), highlighting context-dependent relationships. The model demonstrated good fit (Pseudo $R^2 = 0.310$, $\chi^2(21) = 47.21$, $p < 0.001$).

Demographic Factors emerged as significant predictors of greenwashing identification in the more complex models. In both linear and logistic regression, the medium demographic category showed significantly lower potential greenwashing identification ($\beta = -1.236$, $p < 0.01$ in linear regression; coefficient = -4.560, $p < 0.05$ in logistic regression). The high demographic category showed a marginally significant negative effect in logistic regression (coefficient = -2.100, $p < 0.10$). These findings suggest that sociodemographic characteristics influence how individuals perceive and evaluate environmental claims in financial communications.

Risk-taking orientation demonstrated significant effects in the more complex models; High risk-taking was associated with significantly lower greenwashing identification in logistic regression (coefficient = -2.856, $p < 0.05$ in Model 3). This relationship was strongly moderated by ESG version, with a significant positive interaction effect (coefficient = 5.424, $p < 0.01$). This suggests that risk attitudes play an important role in shaping perceptions of greenwashing, with effects that vary depending on the experimental context.

Gender emerged as a significant moderator in the most complex model (Model 4). While gender alone did not show a significant main effect, the interaction between gender (male) and ESG version was significant and negative (coefficient = -3.495, $p < 0.05$). This suggests that gender differences in greenwashing identification are context-dependent, with males exhibiting distinct patterns of identification compared to females, particularly in the ESG version condition.

Attention to contradiction (ambiguity) in screen 3 and ESG Version Interaction; The interaction between high ESG contradiction detection and ESG version showed an interesting pattern. In simpler models, the interaction approached significance (coefficient = 1.224, $p < 0.10$ in Model 1). This effect weakened in more complex models, suggesting individual characteristics may partially explain it. This indicates that the relationship between contradiction detection and greenwashing identification is moderated by both experimental conditions and individual differences.

The explanatory power of the models increased substantially with the addition of predictors. This progression demonstrates that the comprehensive models incorporating ESG components, personal characteristics, and gender explain a substantial portion of the variance in greenwashing identification. These results reveal additional complexity in the relationships between expert traits and the detection of greenwashing. The results demonstrate that while visual attention to contradictions is necessary for identifying greenwashing, the translation of attention into a critical assessment is moderated by individual characteristics and contextual factors, thereby extending our understanding of the "say-do gap" detection process among financial experts.

Table 1: Multiple Regression Analysis Predicting Greenwashing Identification

Variable	Model 1	Model 2*
Total RelativeFixation on ESG Contradictions	2.162**	2.276*
	(1.021)	(1.215)
PC1: Environmental Action Orientation		
Medium		-0.255
		(0.461)
High		-0.307
		(0.530)
PC2: Media and Regulatory Influence		
Medium		-0.858*
		(0.483)
High		-1.085**
		(0.521)
PC3: Governance and ESG Data Engagement		
Medium		0.234
		(0.507)
High		-0.171
		(0.544)
PC4: Climate Risk and Economic Evaluation		
Medium		0.316
		(0.503)
High		0.965

		(0.622)
ESG Version		-0.825
		(0.968)
Interaction Terms		Included
Control Variables		
Demographic Category		0.011
		(0.165)
Risk-Taking Category		0.153
		(0.153)
Risk Perception Category		0.029
		(0.231)
Constant	2.389***	2.284**
	(0.502)	(1.042)
Observations	127	112
R^2	0.035	0.237
Adjusted R^2	0.027	0.059
F-statistic	4.48**	1.33

Note: Table presents linear regression coefficients with standard errors in parentheses. Model 1 presents a simple regression with total fixation on ESG contradictions (ambiguity) as the sole predictor. Model 2* includes all ESG-related personality components, experimental condition, interaction terms, and control variables. Interaction terms between each component and ESG Version are included in the model but not displayed individually for clarity. Standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 2: Multiple Regression models Analysis Predicting Greenwashing Identification

Variable	Model 1	Model 2	Model 3	Model 4
Attention Measures				
High Fixation on ESG Contradiction	0.212	0.254	0.291	0.124
	(0.299)	(0.300)	(0.333)	(0.354)
ESG Version	-0.250	-1.349	-2.123†	-1.432
	(0.289)	(0.841)	(1.120)	(1.224)
High Contradiction × ESG	0.822†	0.662	0.500	0.077
	(0.438)	(0.444)	(0.503)	(0.519)
ESG Components				
PC2: Media Influence (Medium)		-0.795†	-1.208*	-1.217*
		(0.428)	(0.490)	(0.513)
PC2: Media Influence (High)		-0.664	-1.327**	-1.222*
		(0.448)	(0.507)	(0.522)
PC4: Climate Risk (Medium)		-0.100	0.947†	0.919†

		(0.418)	(0.525)	(0.544)
PC4: Climate Risk (High)		0.500	1.213†	1.217†
		(0.518)	(0.617)	(0.658)
Demographics				
Demographic Category (Medium)			-1.236**	-1.321**
			(0.444)	(0.477)
Perception Risks Category (Very High)			1.455	1.603†
			(0.906)	(0.923)
Gender (Male)				0.499
				(0.384)
Constant	3.303***	4.182***	4.347***	3.965***
	(0.211)	(0.542)	(0.806)	(0.890)
Model Statistics				
Observations	127	127	112	111
R^2	0.082	0.257	0.394	0.373
F-statistic	3.65*	1.95*	1.68*	1.39
Prob > F	0.015*	0.017*	0.034*	0.122

Note: Table presents linear regression coefficients with standard errors in parentheses. Model 1 includes only high ESG contradiction fixation, ESG version, and their interaction. Model 2 adds ESG component categories (PC1-PC4) and their interactions with ESG version. Model 3 incorporates demographic categories and their interactions. Model 4 includes gender variables. Reference categories are: Low (for PC1, PC2, PC3, PC4 and demographic categories) and Female (for gender). † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 3: Logistic Regression Models for Predicting High Greenwashing Identification

Variable	Coefficient	Standard Error	Odds Ratio
High Fixation on ESG Contradictions	1.409**	0.573	4.09**
PC1: Environmental Action Orientation			
Medium	-0.349	0.991	0.71
High	-0.095	1.213	0.91
PC2: Media and Regulatory Influence			
Medium	-3.810**	1.626	0.02**
High	-4.215**	1.652	0.01**
PC3: Governance and ESG Data Engagement			
Medium	-0.416	1.057	0.66
High	-2.194*	1.254	0.11*
PC4: Climate Risk and Economic Evaluation			
Medium	3.879**	1.818	48.37**
High	5.105**	2.316	164.86**

ESG Version	-1.898	2.307	0.15
Significant Interaction Terms			
PC2 Medium × ESG Version	3.473*	1.950	32.23*
PC3 High × ESG Version	4.440**	1.806	84.74**
Control Variables			
Demographic Category	-0.201	0.332	0.82
Risk-Taking Category	0.251	0.328	1.29
Risk Perception Category	0.074	0.467	1.08
Constant	-1.032	2.204	0.36
Observations	112		
Pseudo R^2	0.310		
LR $Chi^2(21)$	47.21***		

Note: *p < 0.10, **p < 0.05, ***p < 0.01. The logistic regression predicts the binary outcome of high greenwashing identification. Odds ratios represent the change in odds of high greenwashing identification for each predictor. Only significant interaction terms are displayed for clarity. The full model includes all interaction terms between each component and ESG Version.

Table 4: Logistic Regression detailed Models for Predicting High Greenwashing Identification

Variable	Model 1	Model 2	Model 3	Model 4
High ESG Contradiction	0.123	0.147	**2.880***	**2.566†**
	(0.496)	(0.555)	(1.359)	(1.351)
ESG Version	-0.349	-2.853	**-9.518***	**-8.549***
	(0.491)	(1.935)	(3.963)	(4.316)
High Contradiction × ESG	**1.224†**	**1.555†**	-1.056	-0.463
	(0.742)	(0.913)	(1.736)	(1.802)
PC1 (Environmental Action)				
Medium		-0.299	0.171	-0.882
		(0.767)	(1.238)	(1.473)
High		-0.814	-0.184	-1.109
		(0.900)	(1.406)	(1.641)
PC1 × ESG				
Medium × ESG		1.279	1.841	2.445
		(1.272)	(2.202)	(2.517)
High × ESG		-0.659	-0.752	-0.419
		(1.425)	(2.356)	(2.756)
PC2 (Media Influence)				
Medium		-1.753*	-6.779**	-6.231**

		(0.891)	(2.412)	(2.290)
High		-1.078	-6.615**	-6.029**
		(0.859)	(2.445)	(2.300)
PC2 × ESG				
Medium × ESG		0.678	7.130*	6.915*
		(1.324)	(2.811)	(2.918)
High × ESG		-1.571	3.186	2.531
		(1.406)	(3.014)	(3.017)
PC3 (Governance)				
Medium		-0.890	-0.719	-0.160
		(0.855)	(1.278)	(1.325)
High		-1.354	-4.057*	-3.314*
		(0.963)	(1.672)	(1.683)
PC3 × ESG				
Medium × ESG		1.248	2.184	2.054
		(1.277)	(1.904)	(2.089)
High × ESG		2.657†	7.617**	8.329**
		(1.424)	(2.569)	(3.126)
PC4 (Climate Risk)				
Medium		0.794	6.941*	6.335*
		(0.847)	(2.702)	(2.539)
High		1.808†	6.640*	6.942*
		(1.090)	(2.908)	(2.876)
PC4 × ESG				
Medium × ESG		0.583	-6.386*	-5.648†
		(1.289)	(3.026)	(2.909)
High × ESG		1.311	-3.012	-3.309
		(1.555)	(3.395)	(3.403)
Demographic Category				
Medium			-4.560*	-4.549*
			(1.792)	(1.863)
High			-2.100†	-2.198†
			(1.199)	(1.314)
Demographic × ESG				

Medium × ESG			3.218	2.750
			(2.220)	(2.478)
High × ESG			2.002	2.413
			(1.671)	(1.774)
Risk Taking Category				
Medium			-0.607	-0.905
			(1.334)	(1.460)
High			-2.856*	-2.356†
			(1.411)	(1.438)
Risk Taking × ESG				
Medium × ESG			2.639	3.680
			(1.974)	(2.334)
High × ESG			5.424**	5.736**
			(1.933)	(2.211)
Perception Risks Category				
High			-1.021	-0.739
			(0.985)	(1.051)
Very High			1.400	1.123
			(1.889)	(2.173)
Perception Risks × ESG				
High × ESG			3.557*	3.613†
			(1.732)	(1.907)
Very High × ESG			(omitted)	(omitted)
			-	-
Gender (Male)				1.785
				(1.129)
Gender × ESG				-3.495*
				(1.686)
Constant	-0.305	0.997	2.783	1.652
	(0.352)	(1.080)	(2.537)	(2.610)
Model Statistics				
Observations	128	128	110	109
LR Chi^2	6.48	38.95	67.81	71.91
Prob > Chi^2	0.090†	0.005**	0.000***	0.000***

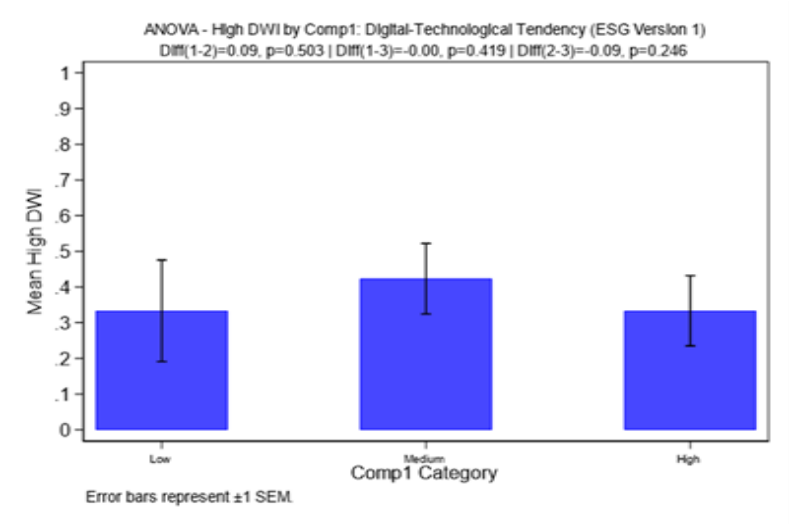
Pseudo R^2	0.037	0.221	0.452	0.484

Note: Table presents logistic regression coefficients with standard errors in parentheses. Model 1 includes only high ESG contradiction fixation, ESG version, and their interaction. Model 2 adds ESG component categories (PC1-PC4) and their interactions with ESG version. Model 3 incorporates demographic categories and their interactions. Model 4 includes gender variables. Reference categories are: Low (for PC1, PC2, PC3, PC4 and demographic categories) and Female (for gender). † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix 5B: Trait Effects on Digital Washing Identification - Detailed Analysis (RQ1&RQ4)

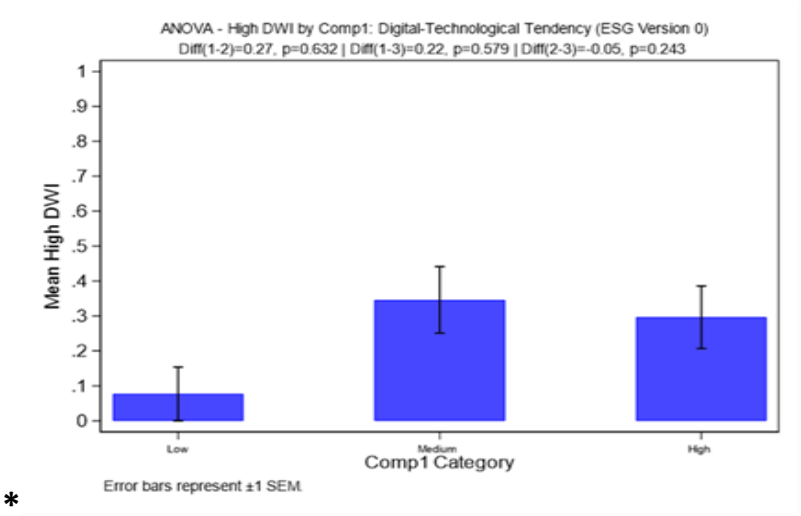
Digital Components and Digital Washing Identification

Figure 1 : ANOVA Analysis of High Digital Washing Identification by Digital-Technological Tendency (ESG Version 1)



Note: Figure 1 presents the ANOVA results examining the relationship between Digital Technological Tendency (Component 1) and high digital washing identification under ESG Version 1 conditions. The bar chart displays mean high digital washing identification scores across low, medium, and high categories of Component 1. The analysis reveals no statistically significant differences between categories (Diff(1-2)=0.09, p=0.503; Diff(1-3)=0.00, p=0.419; Diff(2-3)=-0.09, p=0.246). The medium category shows slightly higher identification rates (M≈0.42) compared to low and high categories (both M≈0.33), though these differences fail to reach statistical significance. Error bars represent ±1 standard error of the mean, indicating considerable variability within each category. These findings suggest that digital-technological tendency does not significantly influence digital washing identification when participants are exposed to ESG Version 1 materials.

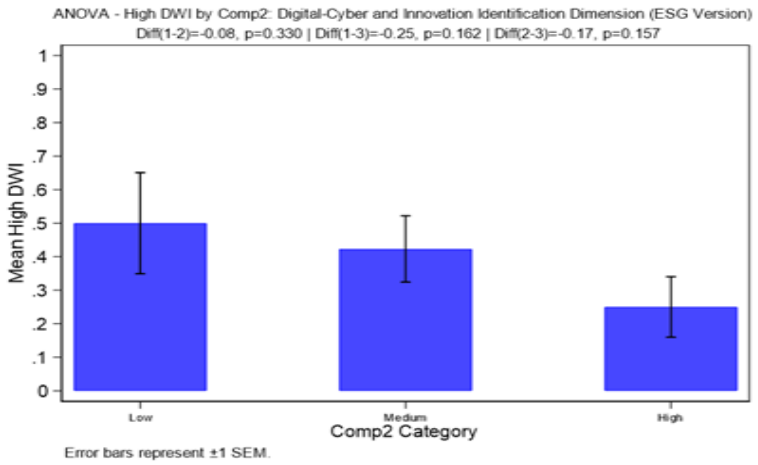
Figure 2 : ANOVA Analysis of High Digital Washing Identification by Digital-Technological Tendency (ESG Version 0)



*

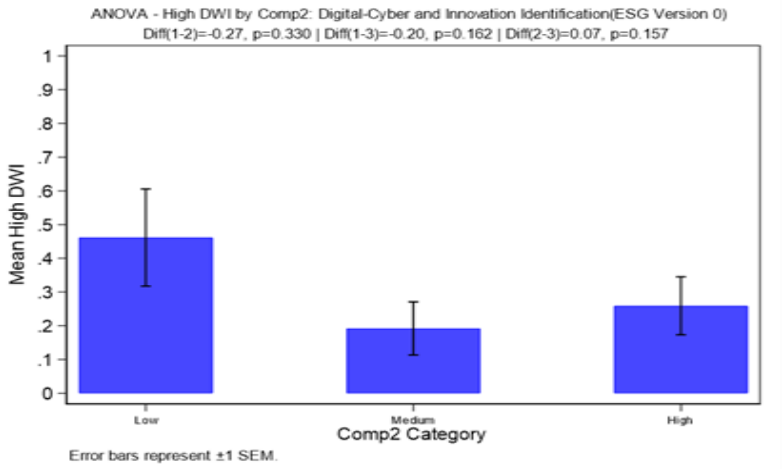
Note: Figure 2 illustrates the ANOVA results examining the relationship between Digital Technological Tendency (Component 1) and high digital washing identification under ESG Version 0 conditions. The bar chart shows mean high digital washing identification scores across low, medium, and high categories of Component 1. The analysis indicates no statistically significant differences between categories (Diff(1-2)=0.27, p=0.632; Diff(1-3)=0.22, p=0.579; Diff(2-3)=-0.05, p=0.243). However, a notable pattern emerges where participants with medium (M≈0.35) and high (M≈0.30) levels of digital technological tendency demonstrate substantially higher digital washing identification compared to those with low levels (M≈0.08). Error bars represent ±1 standard error of the mean. These findings suggest that while not statistically significant, there may be a threshold effect where a minimum level of digital-technological tendency is necessary for effective digital washing identification under Innovation version (ESG Version 0) conditions.

Figure 3 : ANOVA Analysis of High Digital Washing Identification by Digital-Cyber and Innovation Identification Dimension (ESG Version 1)



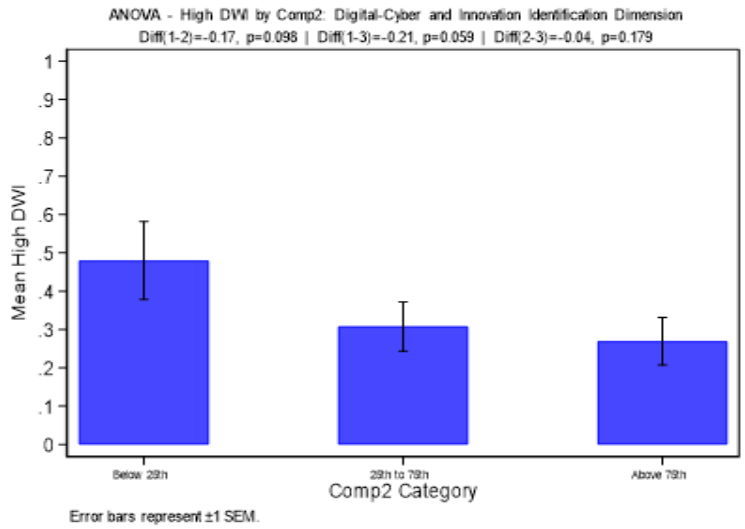
Note: Figure 3 presents the ANOVA results examining the relationship between Digital-Cyber identification and Innovation Identification Dimension (Component 2) and high digital washing identification under ESG Version 1 conditions. The bar chart displays mean high digital washing identification scores across low, medium, and high categories of Component 2. The analysis reveals no statistically significant differences between categories (Diff(1-2)=-0.08, p=0.330; Diff(1-3)=-0.25, p=0.162; Diff(2-3)=0.17, p=0.157). Interestingly, there appears to be an inverse relationship pattern, with low Component 2 scores associated with higher digital washing identification (M≈0.50) compared to medium (M≈0.42) and high (M≈0.25) categories. Error bars represent ±1 standard error of the mean. These findings suggest that heightened awareness of digital-cyber issues and innovation identification may paradoxically reduce sensitivity to digital washing under ESG Version 1 conditions, though this trend does not reach statistical significance.

Figure 4: ANOVA Analysis of High Digital Washing Identification by Digital-Cyber and Innovation Identification Dimension (ESG Version 0)



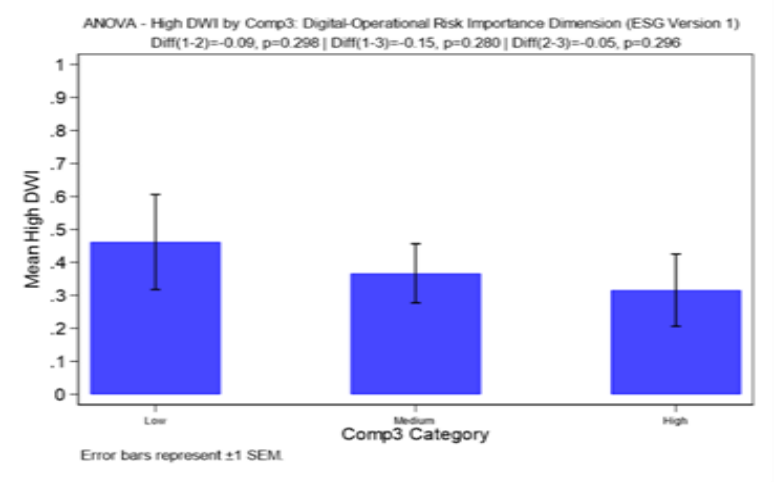
Note: Figure 4 illustrates the ANOVA results examining the relationship between Digital-Cyber identification and Innovation Identification Dimension (Component 2) and high digital washing identification under ESG Version 0 conditions. The bar chart shows mean high digital washing identification scores across low, medium, and high categories of Component 2. The analysis indicates no statistically significant differences between categories (Diff(1-2)=0.27, p=0.330; Diff(1-3)=0.20, p=0.162; Diff(2-3)=0.07, p=0.157). However, a clear pattern emerges where participants with low levels of Component 2 demonstrate substantially higher digital washing identification (M≈0.47) compared to those with medium (M≈0.20) and high (M≈0.25) levels. Error bars represent ±1 standard error of the mean. These findings suggest that, similar to ESG Version 1 conditions, heightened digital-cyber awareness may paradoxically reduce sensitivity to digital washing under ESG Version 0 conditions, potentially indicating a "skepticism paradox" where greater domain knowledge leads to less critical evaluation of digital washing claims.

Figure 5: ANOVA Analysis of High Digital Washing Identification by Digital-Cyber and Innovation Identification Dimension (all samples)



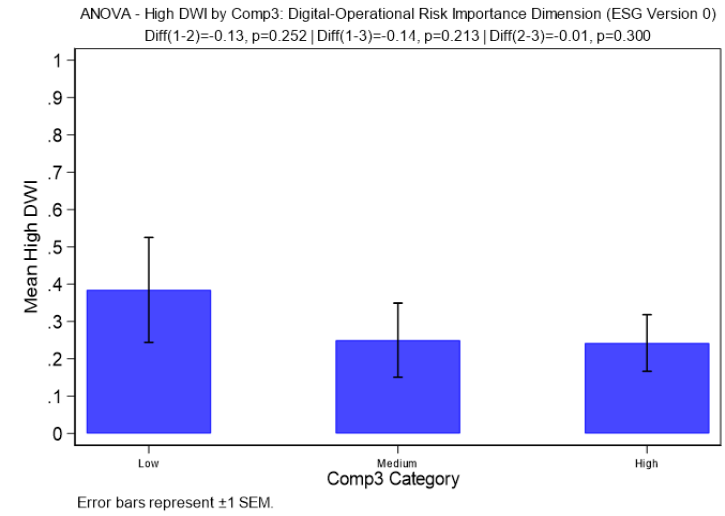
Note: Figure 5 presents the ANOVA results examining the relationship between Digital-Cyber identification and Innovation Identification Dimension (Component 2) and high digital washing identification. The bar chart displays mean high digital washing identification scores across three categories of Component 2. The analysis reveals marginally significant differences between categories (Diff(1-2)=0.17, p=0.098; Diff(1-3)=0.21, p=0.059; Diff(2-3)=0.04, p=0.179). A clear downward trend is visible, with low Component 2 scores associated with substantially higher digital washing identification (M≈0.45) compared to medium (M≈0.30) and high (M≈0.25) categories. Error bars represent ±1 standard error of the mean. These findings suggest that heightened awareness of digital-cyber issues and innovation identification may paradoxically reduce sensitivity to digital washing, approaching statistical significance particularly between low and high categories (p=0.059). This pattern aligns with the "skepticism paradox" observed in other analyses, where greater domain knowledge in digital-cyber areas may lead to less critical evaluation of digital washing claims, potentially due to increased tolerance for technical ambiguity or overconfidence in personal assessment abilities.

Figure 6: ANOVA Analysis of High Digital Washing Identification by Digital-Operational Risk Importance Dimension (ESG Version 1)



Note: Figure 6 presents the ANOVA results examining the relationship between Digital Operational Risk Importance Dimension (Component 3) and high digital washing identification under ESG Version 1 conditions. The bar chart displays mean high digital washing identification scores across low, medium, and high categories of Component 3. The analysis reveals no statistically significant differences between categories (Diff(1-2)=0.09, p=0.298; Diff(1-3)=0.15, p=0.280; Diff(2-3)=0.05, p=0.296). However, a clear downward trend is visible, with low Component 3 scores associated with higher digital washing identification (M≈= 0.45) compared to medium (M≈= 0.37) and high (M≈= 0.31) categories. Error bars represent ±1 standard error of the mean. These findings suggest that increased awareness of digital-operational risks may reduce sensitivity to digital washing under ESG Version 1 conditions, potentially indicating that a focus on operational risk may direct attention away from communication inconsistencies.

Figure 7: ANOVA Analysis of High Digital Washing Identification by Digital-Operational Risk Importance Dimension (ESG Version 0)



Note: Figure 7 illustrates the ANOVA results examining the relationship between Digital Operational Risk Importance Dimension (Component 3) and high digital washing identification under ESG Version 0 conditions. The bar chart shows mean high digital washing identification scores across low, medium, and high categories of Component 3. The analysis indicates no statistically significant differences between categories (Diff(1-2)=0.13, p=0.252; Diff(1-3)=0.11, p=0.213; Diff(2-3)=0.01, p=0.300). Similar to ESG Version 1 conditions, a downward trend is visible, with low Component 3 scores associated with higher digital washing identification (M≈0.38) compared to medium (M≈0.25) and high (M≈0.24) categories. Error bars represent ±1 standard error of the mean. These findings reinforce the pattern observed under ESG Version 1 conditions,

suggesting that across experimental conditions, increased focus on digital-operational risks may consistently reduce sensitivity to digital washing, potentially due to attention allocation toward operational rather than communication aspects of digital information.

Digital-Cyber and Innovation Identification (PC2) demonstrates a consistent negative relationship with potential digital washing identification across conditions, with the overall sample showing a marginally significant difference between low and high awareness groups ($p = 0.059$).

Linear regression models demonstrate that high Digital-Technological Tendency (PC1) is positively associated with potential digital washing identification ($\beta = 0.357$, $p < 0.05$), suggesting individuals with greater technological orientation may be more sensitive to potential digital washing claims. Conversely, Digital-Cyber and Innovation Identification (PC2) shows consistent negative relationships across models, though not reaching statistical significance in linear models.

Logistic regression models provide more substantial evidence for these relationships. High innovation contradiction detection is significantly negatively associated with high potential digital washing identification ($\beta = -0.131$, $p < 0.05$), indicating participants who detected innovation contradictions were less likely to identify potential digital washing. This counterintuitive finding suggests potential "innovation bias," wherein greater attention to innovation contradictions may paradoxically reduce sensitivity to potential digital washing claims. Digital-Cyber and Innovation Identification (PC2) demonstrates a significant negative relationship with high-potential digital washing identification, particularly for the medium category ($\beta = -2.524$, $p < 0.05$), suggesting that moderate cyber-innovation awareness may hinder detection. Gender differences emerge, with males showing a marginally higher potential for digital washing identification ($\beta = 0.953$, $p < 0.10$). Model fit improves substantially with Pseudo R^2 increasing from 0.014 to 0.274.

RQ4a reveals a complex "paradox of expertise" in how individual traits influence both potential greenwashing and digital washing detection. For potential greenwashing identification, visual attention to contradictions consistently predicts success (OR = 4.09, $p < 0.05$), Media and Regulatory Influence demonstrates "skepticism paradox" where lower awareness leads to superior detection (OR = 0.01, $p < 0.05$), while Climate Risk awareness shows robust positive effects (OR = 164.86, $p < 0.05$). For potential digital washing identification, different patterns emerge: Digital-Technological Tendency shows positive associations ($\beta = 0.357$, $p < 0.05$), but Digital-Cyber and Innovation Identification reveals "innovation bias" where medium awareness inhibits detection ($\beta = -2.524$, $p < 0.05$). These findings reveal domain-specific cognitive mechanisms, suggesting effective washing detection depends not on maximum expertise levels but on optimal combinations of traits, contextual alignment, and domain-appropriate information processing capabilities.

Table 1: Linear Regression Models Predicting Digital Washing Identification

Variable	Model 1	Model 2	Model 3	Model 4
High Innovation Contradiction Fixation	-0.293	-0.194	-0.197	-0.242
	(0.303)	(0.323)	(0.366)	(0.379)
ESG Version	0.096	-0.231	-0.716	-0.533
	(0.330)	(0.795)	(1.173)	(1.189)
High Contradiction × ESG	0.322	0.223	0.058	0.039

	(0.439)	(0.469)	(0.533)	(0.547)
PC1 (Digital-Technological)				
Medium		0.499	0.428	0.296
		(0.431)	(0.458)	(0.461)
High		0.667	0.357*	0.241*
		(0.463)	(0.531)	(0.534)
PC1 × ESG				
Medium × ESG		-0.366	-0.321	-0.217
		(0.652)	(0.724)	(0.724)
High × ESG		-0.410	-0.411	-0.330
		(0.703)	(0.798)	(0.798)
PC2 (Digital-Cyber)				
Medium		-0.797	-1.040	-1.024
		(0.451)	(0.515)	(0.512)
High		-0.657	-0.826	-0.844
		(0.442)	(0.540)	(0.548)
PC2 × ESG				
Medium × ESG		0.563	0.784	0.828
		(0.667)	(0.747)	(0.747)
High × ESG		0.131	0.496	0.605
		(0.655)	(0.805)	(0.816)
PC3 (Digital-Operational)				
Medium		-0.432	-0.301	-0.113
		(0.459)	(0.487)	(0.499)
High		-0.473	-0.325	-0.192
		(0.449)	(0.505)	(0.515)
PC3 × ESG				
Medium × ESG		0.341	0.330	0.092
		(0.639)	(0.711)	(0.720)
High × ESG		0.762	0.986	0.827
		(0.781)	(0.930)	(0.932)
Demographic Category				
Medium			-0.466	-0.465
			(0.435)	(0.474)
High			-0.536	-0.568

			(0.509)	(0.531)
Demographic × ESG				
Medium × ESG			-0.514	-0.552
			(0.670)	(0.695)
High × ESG			-0.319	-0.398
			(0.688)	(0.718)
Gender (Male)				0.000
				(0.000)
Gender × ESG				0.000
				(0.000)
Constant	3.303***	4.182***	4.347***	4.347***
	(0.211)	(0.542)	(0.806)	(0.806)
Model Statistics				
Observations	128	128	112	111
F-statistic	0.82	0.72	1.05	1.05
Prob > F	0.048*	0.076†	0.413	0.419
R^2	0.020	0.088	0.253	0.273
Adjusted R^2	-0.004	-0.034	0.013	0.013
Root MSE	1.228	1.246	1.247	1.239

Note: Table presents unstandardized coefficients with standard errors in parentheses. Model 1 includes only high innovation contradiction, ESG version, and their interaction. Model 2 adds digital component categories (PC1-PC3) and their interactions with ESG version. Model 3 incorporates demographic categories and their interactions. Model 4 includes gender variables. Reference categories are: Low (for PC1, PC2, PC3, and demographic categories) and Female (for gender). † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 2: Logistic Regression Models Predicting High Digital Washing Identification

Variable	Model 1	Model 2	Model 3	Model 4
High Innovation Contradiction Fixation	-0.475	-0.367	-0.131*	-0.403*
	(0.557)	(0.630)	(0.773)	(0.839)
ESG Version	0.167	0.720†	1.838	2.891
	(0.567)	(1.595)	(2.682)	(2.863)
High Contradiction × ESG	0.553	0.623†	-0.257	0.014
	(0.773)	(0.859)	(1.132)	(1.178)
PC1 (Digital-Technological)				
Medium		2.189	2.510	2.435
		(1.193)	(1.388)	(1.423)
High		2.106	1.758	1.879
		(1.237)	(1.412)	(1.495)

PC1 × ESG				
Medium × ESG		-1.843	-2.202	-2.127
		(1.462)	(1.782)	(1.809)
High × ESG		-1.940	-2.617	-2.738
		(1.532)	(1.885)	(1.948)
PC2 (Digital-Cyber)				
Medium		-1.580	-2.524*	-2.417*
		(0.878)	(1.240)	(1.208)
High		-1.173†	-0.822	-0.726
		(0.808)	(1.065)	(1.106)
PC2 × ESG				
Medium × ESG		1.147†	1.764	1.659
		(1.192)	(1.641)	(1.625)
High × ESG		-0.030	-1.076	-1.168
		(1.161)	(1.675)	(1.723)
PC3 (Digital-Operational)				
Medium		-0.768	0.400	0.877
		(0.884)	(1.123)	(1.207)
High		-0.955	-0.244	-0.012
		(0.866)	(1.076)	(1.205)
PC3 × ESG				
Medium × ESG		0.588	-0.096	-0.577
		(1.145)	(1.513)	(1.607)
High × ESG		0.968	2.088	1.852
		(1.372)	(1.967)	(2.058)
Demographic Category				
Medium			-1.084	-1.095
			(0.941)	(1.040)
High			-0.669	-0.513
			(1.145)	(1.187)
Demographic × ESG				
Medium × ESG			-0.849	-0.837
			(1.446)	(1.515)
High × ESG			-1.535	-1.535
			(1.552)	(1.552)

Gender (Male)				0.953†
				(0.956)
Gender × ESG				-0.944
				(1.230)
Constant	-0.305	0.997	2.783	1.652
	(0.352)	(1.080)	(2.537)	(2.610)
Model Statistics				
Observations	128	128	112	111
Pseudo R^2	0.014	0.091	0.259	0.274
LR Chi^2	2.17	14.58	35.98	37.46
Prob > Chi^2	0.537	0.482	0.072†	0.087†
Log likelihood	-79.183	-72.981	-51.424	-49.604

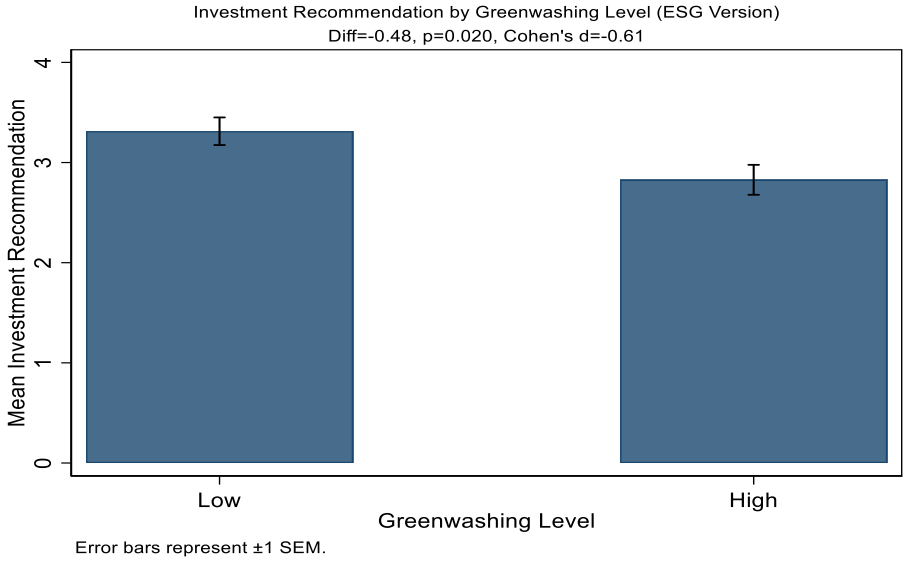
Note: Table presents logistic regression coefficients with standard errors in parentheses. Model 1 includes only high innovation contradiction, ESG version, and their interaction. Model 2 adds digital component categories (PC1-PC3) and their interactions with ESG version. Model 3 incorporates demographic categories and their interactions. Model 4 includes gender variables. Reference categories are: Low (for PC1, PC2, PC3, and demographic categories) and Female (for gender). † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix 6: Washing Identification and Investment Recommendation (RQ2&RQ4)

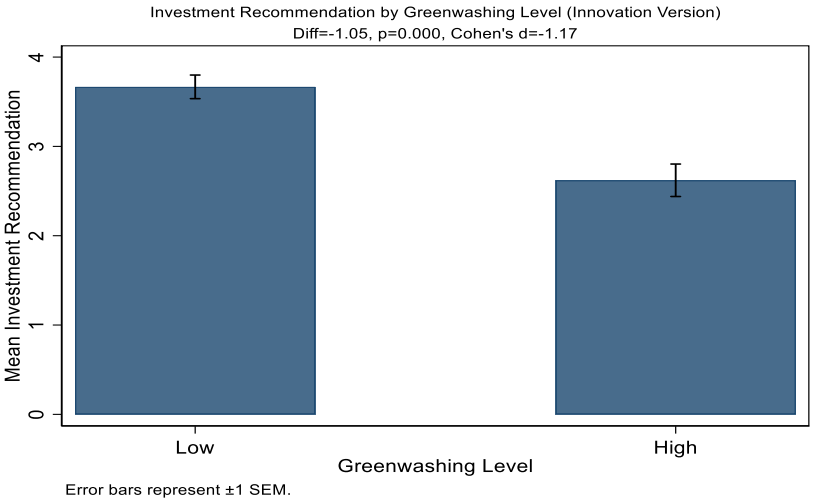
T - tests visualization:

Figures 1 a - d: Potential Washing Identification Impact on Investment Recommendation

Figures 1 a – b: Potential Greenwashing Identification and Investment Recommendation

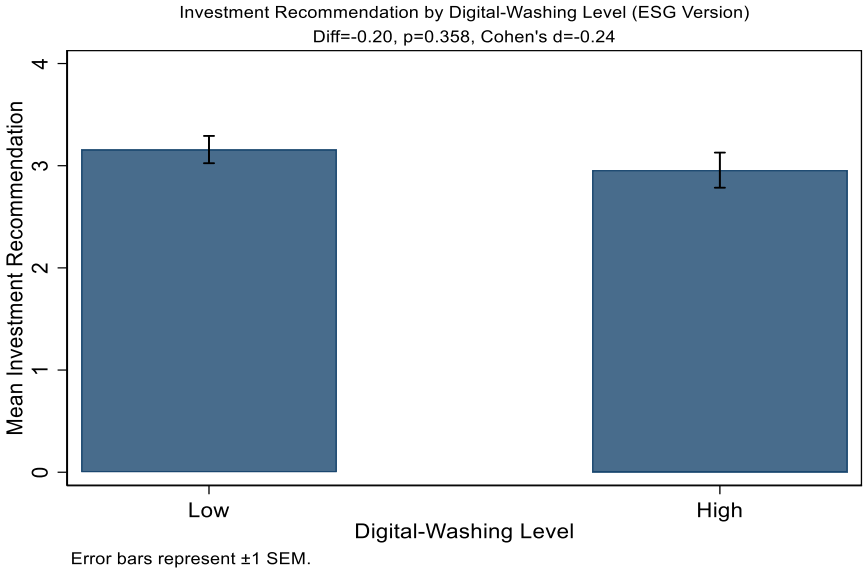


Note: Figure 1 –a shows significantly lower investment recommendation scores for participants with high greenwashing identification level (ESG version) compared to those with low greenwashing identification level (diff=0.48, p=0.020, Cohen's d=0.61), indicating that higher perceived greenwashing negatively impacts investment recommendations during ESG treatment on Screen 1.

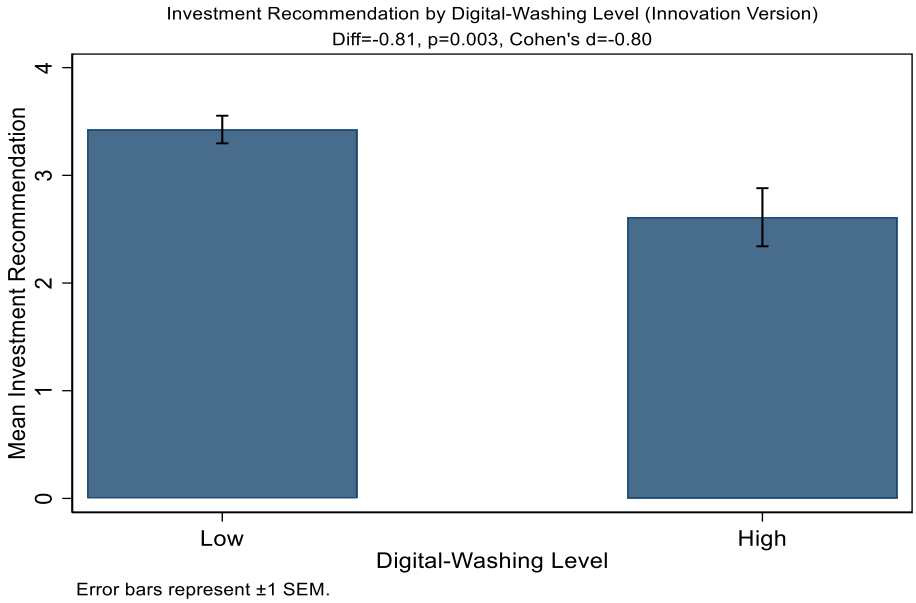


Note: Figure 1- b shows significantly lower investment recommendation scores for participants with high greenwashing identification level (Innovation version) compared to those with low greenwashing identification level (diff=1.05, p=0.000, Cohen's d=1.17), indicating a strong negative impact of perceived greenwashing on investment recommendations with a large effect size during Innovation treatment on Screen 1.

Figures 1 c-d: Potential Digital Washing Identification and Investment Recommendation



Note: Figure 1- c shows no significant difference in investment recommendation scores between participants with high digital-washing identification level and those with low digital-washing identification level in the ESG version (diff=0.20, p=0.358, Cohen's d=0.24), indicating that perceived digital-washing has minimal impact on investment recommendations in the context of ESG treatment on Screen 1.



Note: Figure 1-d shows significantly lower investment recommendation scores for participants with high digital-washing identification level compared to those with low digital-washing identification level in the Innovation version (diff=0.81, p=0.003, Cohen's d=0.80), indicating that perceived digital-washing has a strong negative impact on investment recommendations in the context of innovation treatment on Screen1.

Model analysis:

Table 1: Linear Regression Models Predicting Investment Recommendation Revision (Greenwashing)

Variable	Model 1	Model 2	Model 3	Model 4
High Greenwashing Identification	-1.046***	-1.067***	-1.175***	-1.224***
	(0.209)	(0.216)	(0.278)	(0.277)
ESG Version	-0.354†	-0.147	-0.017	-0.077
	(0.204)	(0.588)	(0.808)	(0.793)
High Greenwashing × ESG	0.561†	0.722*	0.820*	0.934*
	(0.300)	(0.327)	(0.397)	(0.389)
PC1 (Environmental Action)				
Medium		0.221	0.310	0.414
		(0.273)	(0.311)	(0.306)
High		0.292	0.477	0.521
		(0.307)	(0.367)	(0.356)
PC1 × ESG				
Medium × ESG		0.345	-0.126	-0.142
		(0.412)	(0.488)	(0.474)
High × ESG		0.130	-0.464	-0.468
		(0.445)	(0.533)	(0.513)
PC2 (Media Influence)				
Medium		0.040	-0.261	-0.158
		(0.302)	(0.373)	(0.359)
High		0.060	-0.224	-0.211
		(0.304)	(0.373)	(0.355)
PC2 × ESG				
Medium × ESG		-0.362	0.005	-0.101
		(0.419)	(0.497)	(0.476)
High × ESG		0.014	0.410	0.425
		(0.453)	(0.533)	(0.508)
PC3 (Governance)				
Medium		-0.647*	-0.916**	-1.129***
		(0.310)	(0.345)	(0.340)
High		-0.128	-0.329	-0.630†
		(0.338)	(0.380)	(0.377)

PC3 × ESG				
Medium × ESG		0.765†	1.289**	1.481**
		(0.427)	(0.468)	(0.454)
High × ESG		0.332	0.854	1.055*
		(0.465)	(0.526)	(0.516)
PC4 (Climate Risk)				
Medium		0.722*	1.004*	1.161**
		(0.287)	(0.397)	(0.385)
High		-0.138	-0.039	0.258
		(0.361)	(0.460)	(0.455)
PC4 × ESG				
Medium × ESG		-1.205**	-1.495**	-1.684***
		(0.413)	(0.529)	(0.509)
High × ESG		-0.656	-1.032	-1.323*
		(0.500)	(0.629)	(0.610)
Demographic Category				
Medium			-0.403	-0.667*
			(0.333)	(0.336)
High			-0.172	-0.361
			(0.320)	(0.314)
Demographic × ESG				
Medium × ESG			0.540	0.762†
			(0.460)	(0.453)
High × ESG			-0.063	0.038
			(0.437)	(0.426)
Risk Taking Category				
Medium			-0.131	-0.135
			(0.325)	(0.309)
High			-0.026	-0.052
			(0.285)	(0.272)
Risk Taking × ESG				
Medium × ESG			0.179	0.112
			(0.437)	(0.419)
High × ESG			-0.307	-0.333
			(0.419)	(0.401)

Perception Risks Category				
High			0.218	0.431†
			(0.246)	(0.247)
Very High			0.128	0.380
			(0.613)	(0.590)
Perception Risks × ESG				
High × ESG			-0.509	-0.681†
			(0.369)	(0.362)
Very High × ESG			-0.943	-1.242
			(0.925)	(0.885)
Gender (Male)				0.294
				(0.255)
Gender × ESG				0.051
				(0.355)
Constant	3.667***	3.497***	3.885***	3.745***
	(0.140)	(0.390)	(0.605)	(0.590)
Model Statistics				
Observations	126	126	110	109
F-statistic	10.23	3.25	2.11	2.27
Prob > F	0.000***	0.000***	0.004**	0.002**
R^2	0.201	0.368	0.457	0.499
Adjusted R^2	0.181	0.255	0.241	0.279
Root MSE	0.839	0.800	0.786	0.748

Note: Table presents unstandardized coefficients with standard errors in parentheses. Model 1 includes only high greenwashing, ESG version, and their interaction. Model 2 adds ESG component categories (PC1-PC4) and their interactions with ESG version. Model 3 incorporates personal characteristics (demographic, risk-taking, perception risks) and their interactions. Model 4 adds gender and its interaction with ESG version. Reference categories are: Low (for PC1, PC2, PC3, PC4, demographic, risk-taking, and perception risks categories) and Female (for gender). † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 2: Linear Regression Models Predicting Investment Recommendation Revision (Digital Washing)

Variable	Model 1	Model 2	Model 3	Model 4
High Digital Washing identification	-0.814***	-0.620*	-0.819**	-0.768*
	(0.248)	(0.270)	(0.294)	(0.302)
ESG Version	-0.268	0.315	1.513†	1.298
	(0.195)	(0.593)	(0.817)	(0.833)
High Digital Washing × ESG	0.613†	0.439	0.612	0.563
	(0.343)	(0.365)	(0.411)	(0.417)

Comp1 (Digital-Technological)				
Medium		-0.117	-0.341	-0.316
		(0.325)	(0.323)	(0.323)
High		-0.106	-0.038	-0.045
		(0.345)	(0.370)	(0.371)
Comp1 × ESG				
Medium × ESG		0.061	0.058	0.027
		(0.482)	(0.496)	(0.496)
High × ESG		0.263	-0.061	-0.085
		(0.517)	(0.549)	(0.550)
Comp2 (Digital-Cyber)				
Medium		0.647†	0.577	0.605†
		(0.328)	(0.360)	(0.360)
High		0.488	0.776*	0.734†
		(0.328)	(0.373)	(0.379)
Comp2 × ESG				
Medium × ESG		-0.478	-0.458	-0.433
		(0.482)	(0.515)	(0.516)
High × ESG		-0.373	-0.992†	-0.850
		(0.485)	(0.560)	(0.567)
Comp3 (Digital-Operational)				
Medium		0.622†	0.884**	0.800*
		(0.337)	(0.335)	(0.344)
High		0.441	0.498	0.424
		(0.331)	(0.348)	(0.354)
Comp3 × ESG				
Medium × ESG		-0.398	-0.901†	-0.883†
		(0.464)	(0.489)	(0.497)
High × ESG		-0.521	-0.181	-0.170
		(0.562)	(0.637)	(0.641)
Demographic Category				
Medium			0.542†	0.449
			(0.304)	(0.323)
High			0.669†	0.586
			(0.353)	(0.366)

Demographic × ESG				
Medium × ESG			-0.075	-0.059
			(0.474)	(0.488)
High × ESG			-0.731	-0.783
			(0.486)	(0.504)
Risk Taking Category				
Medium			0.388	0.387
			(0.338)	(0.337)
High			0.615†	0.581†
			(0.318)	(0.319)
Risk Taking × ESG				
Medium × ESG			-0.234	-0.225
			(0.466)	(0.465)
High × ESG			-0.704	-0.668
			(0.456)	(0.456)
Perception Risks Category				
High			0.097	0.161
			(0.258)	(0.275)
Very High			-0.853	-0.733
			(0.652)	(0.663)
Perception Risks × ESG				
High × ESG			-0.424	-0.487
			(0.378)	(0.390)
Very High × ESG			0.598	0.368
			(0.956)	(0.965)
Gender (Male)				0.113
				(0.285)
Gender × ESG				0.272
				(0.390)
Constant	3.426***	2.598***	1.880**	1.912**
	(0.131)	(0.420)	(0.598)	(0.607)
Model Statistics				
Observations	126	126	110	109
F-statistic	4.01	1.34	1.45	1.24
Prob > F	0.009**	0.190	0.102	0.227

R^2	0.090	0.155	0.323	0.312
Adjusted R^2	0.068	0.040	0.101	0.060
Root MSE	0.895	0.909	0.856	0.854

Note: Table presents unstandardized coefficients with standard errors in parentheses. Model 1 includes only high digital washing Identification, ESG version, and their interaction. Model 2 adds digital component categories (Comp1-Comp3) and their interactions with ESG version. Model 3 incorporates personal characteristics (demographic, risk-taking, perception risks) and their interactions. Model 4 adds gender and its interaction with ESG version. Reference categories are: Low (for Comp1, Comp2, Comp3, demographic, risk-taking, and perception risk categories) and Female (for gender). † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.00

Linear regression models examining potential digital washing identification show a consistent negative relationship with investment recommendation revisions across all models, remaining relatively stable from Model 1 (β = -0.814, p < 0.001) to Model 4 (β = -0.768, p < 0.05). This indicates financial experts with high potential digital washing identification tend to downgrade investment recommendations significantly. Effect remains robust after controlling for digital components, personal characteristics, and gender, suggesting potential digital washing detection has direct, independent influence on investment decisions.

The interaction between high potential digital washing identification and ESG version shows a marginally significant positive moderating effect in Model 1 (β = 0.613, p < 0.10). However, this effect weakens and becomes non-significant in more complex Models 2-4 (β = 0.439 to β = 0.563, p > 0.10). This suggests that while there may be some mitigation of the negative impact of potential digital washing in the ESG version condition, this moderating effect is not robust when controlling other factors.

Among digital components, Digital-Cyber identification and Digital-Operational risks exhibit significant relationships with investment recommendation revisions. Findings suggest that awareness of digital components generally leads to more favorable investment recommendations; however, this effect may be reduced when ESG factors are considered.

Personal characteristics show marginally significant effects in Models 3 and 4. High-risk-taking orientation shows a marginally significant positive relationship with investment recommendations in Model 4 (β = 0.581, p < 0.10). Gender does not show significant main or interaction effects (β = 0.113 and β = 0.272, respectively, p > 0.10), suggesting gender differences do not substantially influence the relationship between potential digital washing identification and investment recommendations.

Model fit varies substantially across specifications. Model 1 achieves statistical significance (p < 0.01) but explains only 9.0% of the variance in investment recommendation revisions. Models 2-4 explain more variance (15.5% to 32.3%) but do not achieve conventional statistical significance (p > 0.05), suggesting while individual predictors show significant relationships, models as a whole have limited predictive power.

These findings highlight important differences between the impacts of potential digital washing and potential greenwashing on investment decisions. While both types of potential washing lead to negative investment recommendation revisions, the effect of potential digital washing appears less robust when additional predictors are included, and the moderating effect of ESG contextual framing is weaker. This suggests financial experts may process and respond to potential digital washing claims differently than potential greenwashing claims, with implications for understanding how sustainability and digital transformation narratives influence investment decision-making.

Our comprehensive analysis reveals a complex interplay between individual characteristics, experimental framing, and potential washing identification, with significant downstream effects on investment recommendations. H4a was confirmed through significant correlations between expert traits and washing identification, though relationships were more complex than anticipated. H4b was strongly supported, with clear negative correlations between washing identification and investment recommendations, moderated by expert characteristics and treatment conditions.