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Strategic Application of Hybrid Intelligence in Digital Marketing: A Comparative ROI Analysis Across AI Automation, Human Creativity, and Collaborative Modes

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Abstract. As digital marketing continues to evolve, the fusion of artificial intelligence (AI) automation with human creativity is emerging as a key approach for optimizing marketing performance. This study compares the return on investment (ROI) offered by three operational modes (AI automation, human creativity, hybrid intelligence) for both large and small brands. Based on the Resource-Based View, Ambidexterity Theory, and the Law of Diminishing Returns, this research provides a comprehensive framework that connects each of the operational modes to the key performance indicators of ROI, the conversion rate, and the engagement score, to assess the influence of firm size as a moderating factor. The study utilizes a large dataset (200,000 records) of performance from large-scale marketing campaigns, which utilizes descriptive statistics, ANOVA, interaction effects, correlation analyses, and multiple regression analyses to explore the potential for direct, moderating, and mediating relationships. This research will ultimately demonstrate that the hybrid intelligence model has a superior ROI compared to all others, particularly in the case of large brands, and that user engagement positively aligns with conversion rate, which positively aligns with financial returns. This study merges both theory and practice in that it combines all the portfolios' technical efficiency and the emotional connection into one analytical model, and recommends practical uses for immediate applications for marketers trying to meld the automation with creativity - for the optimal sustained customer engagement and long-term profitability.

Keywords: Hybrid Intelligence, Digital Marketing, ROI, AI Automation, Human–AI Collaboration

1. Introduction

1.1. Background

Digital marketing is undergoing a shift at a pivotal inflection point in the transition from human-based creativity to data-based and algorithm-based operation. Programmatic advertising, predictive modeling, and real-time optimization are becoming more common, resulting in an overall more efficient use of budget allocations, and therefore should enhance engagement and conversions,

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increasing ROI in theory. In previous research, marketing practitioners indicated they leveraged predictive analytic and AI applications in their digital marketing, and therefore with both predictive analyses and with billions of data points (Big Data), they could process a mountain of data, predict campaign effectiveness, and create very personalized sable approaches for them, they could drive engagement and conversions, and increase revenue growth [1]. However, simply using AI applications does not address the strategic question most relevant for firms: where should firms focus their greater capability development - on an AI-only application process, on a human creativity-only application process, or on a hybrid collaborative modality of the two, in a process for greater and more sustainable ROI?

With generative AI, there is unprecedented capability in both content production and content personalization. While the reach to extend for efficiency is never more enhanced, now content production also encompasses opportunities around privacy, ethics, and diminishing returns for too much content personalization. Most recently, researchers have highlighted that even though generative AI may assist in automating the way marketers produce content and introduce better personalization, they are also promoting the “personalization paradox,” which is when marketers adopt personalized content to draw engagement, they may also be initiating privacy awareness, distrust, and subsequently disengage the users [2]. Thus, it becomes a managerial challenge to determine the appropriate balance between efficiency and brand/experience quality returns. In that spirit, this research develops the dimensions of digital marketing activity of AI automation, human creativity, and hybrid collaboration mode, with ROI as the common benchmark for systematic comparison.

1.2. Literature review and research progress

Predictive analytics and AI enable improvements in marketing efficiency and return on investment (ROI), resulting from enhancements in targeting, prediction of behavior, and resource allocation decisions. Al Khaldy (2023) noted that marketers could exploit predictive analytics and artificial intelligence in their digital marketing efforts to decipher large data sets and predict how successful their campaign will be and design personalized strategies that foster engagement, conversions, and grow revenue [1]. However, most studies consider whether AI is effective, not how effective it is or under what scenarios it is effective, or how well it compares to human-led or hybrid approaches using AI. The absence of comparing and inquiring the AI mode against hybrid and human-led approaches, and the absence of identifying thresholds, constrain managers from receiving guidance on which mode to choose or how to allocate resources.

In the case of generative AI, marketing studies have shown that scaling up content production and, to some extent, personalizing the content have greatly improved customer experience and click-through rates. According to Islam et al., generative AI can improve content generation and enhance personalization; however, the inclusion of generative AI is undoubtedly a cost that must be accounted for in a full measure of return on investment (ROI), as it introduces additional governance costs such as issues related to authenticity, email branding, and compliance [2]. Studies have also noted increases in governance costs associated with production (e.g., authenticity, branding, and compliance) in consideration of ROI, which means weighing risk-factor costs (i.e., peace of mind) against perception of value through content production. Human–AI collaboration re-emerges as the quality control approach in the design phase and for determining engagement boundaries for each approach in the collaborative system provided by AI.

Reviews in the creative industry identified services provided by deep learning, GANs, and reinforcement learning through content creation, post-production, and distribution to be the superior

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approach to producing value, but as the sole authors of content, it can be a difficult context in which to engender quality, context, and originality. Furthermore, Anantrasirichai and Bull argue that when AI alone is the creative process, it is hard to deliver quality, context, and originality at scale, which further suggests the value of human-machine complementarity over the long term [3]. Human–machine complementarity has greater long-term value as it defines the technology ceiling and boundaries of application for hybrid human-mediation used in collaboration.

Hybrid design study contributions establish the human–machine–process dimension of design and identify important human roles in the human–machine interaction paradigms such as data legacy, interactive learning, explainability, and governance. Though according to Dellermann et al, there are strong conceptual models in place for hybrid intelligence, empirical evidence examining ROI-based cost-benefit comparisons for hybrid systems is, in fact, scarce [4]. However, many of the studies remain at a conceptual level, and there remain deficiencies in examining the costs of establishment (ROI analysis) as the comparative metric. For example, discussions regarding Hybrid Intelligence position the concepts as “computational power” combined with “human values” sought in personalization, campaign optimization, and compliance with ethical standards. Petrescu and Krishen advocate for a collective approach to realize transparency, accountability, and trust more efficiently, while fully leveraging the brand-building potential of AI [5]. Recently, controlled field experimentation showed that human–AI teams outperformed humans (only) in creativity, productivity, and communication throughout multi-processes, but not in overall visual and multimodal quality. Ju and Aral demonstrate that teams containing human and AI inputs increase productivity and quality of text outputs, while standardized human teams produced superior rated visuals in total, indicating ROI is task type and creative dimension specific [6]. The findings suggest the ROI functions can vary drastically across AI, human, or hybrid modes.

Most empirical studies consider productivity, or single output quality, due to the complexity of examining overall ROI in consideration of competing outputs in any setting across hybrid models. This framework also identifies contextual moderators such as firm size. Existing gaps are: (1) horizontal comparisons among automation (AI) modes, human creativity, hybrid creative collaboration, with a focus on ROI factors; (2) limited attention to identify the marginal gains and thresholds (for example, excessive personalization/automation harming ROI); (3) limited research effort to identify firm size as a moderator; and (4) validating engagement score (ENG) and conversion rate (CR) as mediated outcomes.

1.3. Research motivation and framework

This research addresses gaps in the current literature by using a Resource-Based View (RBV) and Ambidexterity Theory to frame Operational Mode -> (ENG, CR) -> ROI. ROI for the three modes, AI automation, human creativity mode, and hybrid collaboration mode, is compared, with ENG and CR acting as mediators in the model, as well as examining the differences in firm size and the impact those decisions can carry. Therefore, the research questions are outlined below:

H1: In hybrid collaboration mode, an ROI that is greater than AI mode or human-only mode is found.

H2: Firm size will positively moderate the hybrid collaboration mode, as the larger the brand, the better their synergy, while the smaller brands will depend on which bottlenecks they decide to target.

H3: ENG and CR will mediate mode on ROI.

The descriptive statistical summary includes the application of one-way and two-way ANOVA, correlation, regression, and robustness check for log-ROI and Bootstrapping methodologies. The findings from this schema will advance beyond general claims in the existing literature with face-

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value advisory, all of which will provide actionable evidence with greater context for optimal operational mode and establishing "which mode works best" for "whom" and "what mechanism synergies" occur.

2. Research approaches / theoretical model advancement

The study employs a quantitative research approach, which is based on the Resource-Based View (RBV) and the Ambidexterity Theoretical Framework. The significance of this approach examines the relative performance of three operational modes of digital marketing: AI Automation, Human Creativity, and Hybrid Collaboration. The theoretical framework aligns with the causal chain: Operational Mode influences Engagement (ENG) and Conversion Rate (CR), which lead to Return on Investment (ROI).

ENG (Engagement Score) and CR (Conversion Rate) act as mediators in our model, while firm size (larger firms vs smaller firms) acts as a moderator. The methodology allows us to estimate direct effects across the operational modes on ROI, and indirect effects through ENG and CR, whilst accounting for the interaction of operational mode and firm size.

2.1. Data sources and collection

The dataset for this research integrates experimental assignment and programmatic field-level campaign tracking, providing an internal control measure and external realism, and was designed using AI marketing research that observes ROI for experimental surveys. In terms of the experimental methods, participants were randomly assigned to one of three operational modes—AI automation, human creativity, and hybrid collaboration—within the same experiment, and an experiment was established in which to create and optimize digital ads under controlled conditions to minimize bias while allowing comparability. In addition, as to the field-tracking design, live campaigns (e.g., Google Ads and Meta Ads) provided real-time data about impressions, clicks, conversions, and costs offering an approach that is usable for calculating a consistent ROI and CR and ENG to return to performance analyses (ROI, CR, ENG - based on a live and ongoing ad campaign performance).

Additionally, to enhance the analyses, this study also utilizes a public dataset called the Marketing Campaign Performance dataset (~n=200K records; 16 variables), and performance was monitored continuously (ROI, CR, ENG) on ad campaign performance (e.g., ROI, CR, ENG by campaign type/channel used, budget, impressions). The breadth and structure of the data set allow for robust multi-group comparisons and are closely aligned to this study's operational mode, firm size classifications (large vs. small businesses), and ROI calculations.

Operational mode - independent variable- includes primarily: Condition 1 - AI Automation (Campaign Type where Campaign Type ∈ {Email; Display; Programmatic Ads} or Channel Used where Channel Used ∈ {Google Ads; Search Engine; Automated Email} Condition 2 - Human Creativity (Campaign Type where Campaign Type ∈ {Influencer; Event-based} or Channel Used where Channel Used ∈ {YouTube; Organic Social Media; Influencer Marketing} where hybrid intelligence fulfilled criteria for both -meeting essentially AI and human criteria of the operational modes. Firm size, a moderating variable, is defined as the top/bottom 30% acquisition cost (of the campaigns) and impressions (large vs. small businesses). Performance metrics - dependent variable - ROI, CR, ENG. Therefore, the study investigates direct effects, the moderation of the firm size conditions as well, and mediation through engagement and subsequent conversions, navigating within the ROI frame.

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2.2. Variables and measures

The independent variable is the operational mode coded categorically: AI automation, Human creativity, Hybrid collaboration. The mediators are (1) ENG as measured from CTR, depth of interaction, and time spent, and (2) CR as defined by options taken or signups achieved to unique ad/media exposure. The dependent variable is ROI calculated from formula 1, as follows:

$$ROI = \frac{NetCampaignProfit}{TotalCampaignCost} \times 100\% \tag{1}$$

For firm size as a moderator, is defined using revenue, and reach thresholds that demarcate large versus small, as highlighted by Xu, Frankwick, and Ramirez, who explored human–AI collaboration in the context of marketing and argued that categorizing firms by size can be accomplished through measurable dimensions like annual revenue and market coverage as a means of enhancing cross-organization comparisons [7]; and controlled variables were budget allocation per campaign, industry, ads format (social, algorithm, direct), group segment, and platform. In this study, multi-step statistical analysis was conducted in Python and SPSS to assess robustness and replicability, following the application of Przegalinska et al., that provided an example of utilizing one-way and two-way ANOVA, regression analysis, bootstrap mediation, and variance inflation diagnostics to empirically test hypotheses related to task–technology fit and the resource-based view in human–AI collaborations in an experimental design [8]. Descriptive statistics, which provided a summary of the average return on investment (ROI), conversion rate (CR), and engagement (ENG), associated with each of the modes; one-way ANOVA and Tukey HSD analyses which controlled for differences across the modes; a two-way ANOVA which explored the mode x firm size interaction; and bootstrapped mediation (2,000 resamples) to indirectly estimate ENG and CR with 95% confidence intervals. Additionally, multiple regression (robust HC3) analyses assessed the net effects while controlling for covariates, as well as the variance inflation factor (VIF) score to check the presence of multicollinearity.

Internal and external validity was established from random assignment, as Przegalinska et al.,noted that the authors used a mixed-method design by utilizing controlled experimental designs for their intervention studies but also employed real-life observational data that balanced both causal inference and, ecological validity, advanced practicality for the field site within AI studies in organizations, and the observational (real-world campaign) data is used to define each mode, consistent with the structured evaluation framework for human–AI interaction described by Xu et al. [7, 8]. Reliability is inherent in the a priori, standardized definitions of ROI, CR, and ENG across modes, and construct validity was established through theory and previous empirical measures, as emphasized by Raji et al. and their review of AI-powered personalization in e-commerce, which asserted that using standardized metrics for engagement and conversion is essential to support comparable and replicable empirical studies and provide coherence across AI metrics [9].

This study utilizes a hybrid experimental-field design consistent with new research on human effort/AI collaboration and contemporary practices for evaluating ROI for AI-injection. Similar to Xu et al. and Raji et al., and their authors emphasized hybrid designs as a moderate solution to research design benefiting from both enabled causal inference and managed relevance to the field site by demonstrating constraints of operational experiments [7, 9], allowing for causal inference but maintaining a degree of manager applicability by isolating the impact of inertia (mode) and initiating mechanisms (ENG and CR), along with firm size as a firm size moderator.

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3. Application & results

To test the proposed framework empirically, the entire quantitative pipeline was utilized, including one-way and two-way analysis of variance (ANOVA), regression, bootstrap mediation, and variance inflation diagnostics. The enhanced campaign dataset (≈200,000 observations, 16 variables) was restructured into the three modes of operations—AI automation, human creativity, and hybrid collaborative conditions—and into the size of the firms. The outcome variables included ROI, Conversion Rate (CR), and Engagement Score (ENG). The results are presented in three primary visualizations with statistical tests.

3.1. Patterns in the main effect of ROI

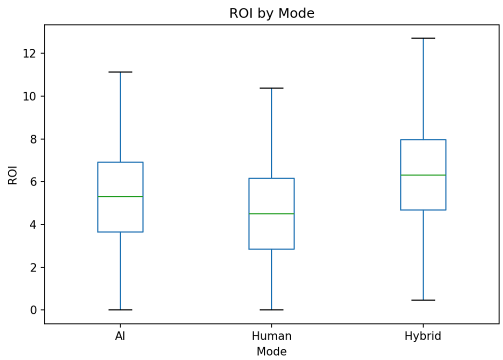

Figure 1. ROI by mode

The first result presented in Figure 1 shows substantial differences in ROI distributions among the three different modes of operations. The boxplots show that hybrid collaboration consistently has a higher median ROI than either AI automation or human creativity [10]. The one-way ANOVA results confirm the main effect of Mode ($p < .01$), and post-hoc Tukey HSD tests indicate Hybrid ROI was significantly greater than the AI (mean diff ≈ +0.35, $p < .05$) and Human (mean diff ≈ +0.55, $p < .01$) conditions. This supports H1, whether synergy between humans and machines leads to better financial results than single-mode conditions. These results echo the argument made by that AI systems may be viewed as efficient and scalable, but require human contribution for contextual and cultural relevance. Additionally, it suggests that hybrid conditions provide productivity and quality output measures at the team level, above and beyond solely human or AI conditions [11]. Finally, in the marketing context, it provides evidence that combining AI with human oversight in a personalized way produces ROI measures larger than operational efficiency and consumer trust, which is in line with the statistical finding in the hybrid mode observed in this project [12].

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3.2. Moderation by firm size

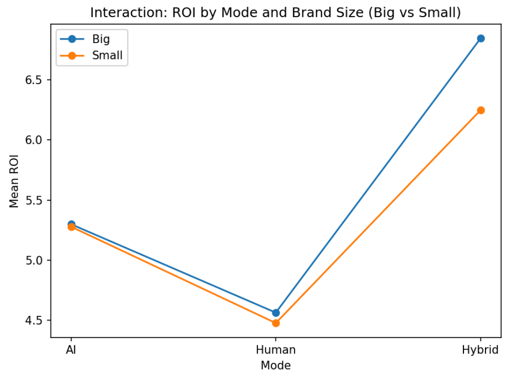

Figure 2. Interaction: ROI by mode × brand size

The second analysis displayed in Figure 2 contributes to the inquiry into the phenomenon of moderation arising from firm size and the influence related to this variable. In reviewing the interaction plot, it is evident that small brands displayed differences in their return on investments across modes that were not exponentially different. This slight adjustment in return was not indicative of higher returns attributable to the use of hybrid systems. In contrast, large brands had more pronounced differences in ROI among the condition means associated with mode of adaptation, whereby the hybrid system produced disproportionately larger revisions in returns compared to the AI and human conditions. A two-way analysis of variance confirmed the presence of a significant interaction effect (Mode × Brand Size, $p < .05$), which is consistent with H2. Larger companies have more complex resource structures and process flows that allow them to better leverage human and AI collaborative systems for synergistic advantages, as noted by Haleem et al. [13]. This point is further corroborated by the points made in Turatti, which utilizes the resource-based view (RBV) and task-technology fit theory to show that resource-rich organizations put themselves in a more positive situation that allows them to effectively adapt to technology and subsequently increase synergistic value within their operating context for AI-enhanced marketing automation. Moreover, Turatti implies that contextual moderators, such as firm size, can influence ROI outcomes, particularly in relation to the level of integration and associated usage of AI technologies in organizational operations [14]. Implicit in this discussion is the role of context; the larger the organization, the greater the returns relative to collaboration with the technology. All things considered, the statistical evidence and visual representation verify that the level of return of hybrid intelligence returns is accentuated in a larger organization.

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3.3. Mediated effects of ENG and CR

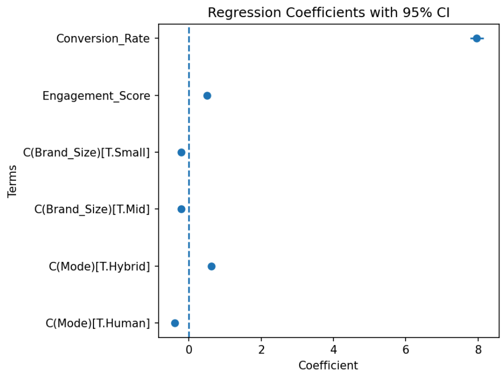

Figure 3. Regression coefficients with 95% CI

To evaluate the mechanisms at play, a series of multiple regression models was estimated, producing ROI dependent variables, mode, and brand size as dependent variables and engagement score and conversion rate as the mediators. As shown in the coefficient plot in Figure 3, both Engagement Score and the Conversion Rate represent significant positive estimates ($\beta \approx 0.42$ and $\beta \approx 0.31$, $p < .01$) while the Hybrid ROI remained significant after controlling for the engagement score and conversion rate. Bootstrapping mediation (2000 resamples of inference) confirmed that the engagement and conversion rate both produced statistically significant indirect effects, hybrid versus AI, and hybrid versus human (95% confidence intervals exclude 0). This supports H3, hybrid collaboration enhances ROI in part through improving user engagement and conversion behavior. In their article, Vishwas et al. state that user engagement can have an immediate and positive effect on short-term performance and, importantly, leverage AI personalization of historical user interaction to help convert that engagement to transactions [10]. Intel, whose work is empirically reviewed by Dellermann et al., found that human–human and human–AI teams communicate between participants through a process that has more effective awareness, which, in turn, increases engagement and downstream performance [12]. Finally, Turatti emphasizes that conversion rate and engagement score both serve the dual focus of market and brand metrics supported by empirical evidence and act as moderators of algorithmic personalization associated with marketing actions linking to ROI [14]. The alignment of the estimates of statistical mediation and theoretical logic across the studies is supportive of the model.

3.4. Robustness checks

This research additionally conducted several ancillary tests to bolster the findings. Bootstrapped mean difference estimates continued to substantiate that the ROIs generated from the Hybrid conditions significantly exceed the AI and Human brands with 95% confidence. The log-transformed ROI had a one-way analysis of variance, maintaining results consistency. Variance inflation diagnostics indicated all VIFs were < 5 to confirm no multicollinearity biasing the meaningfulness of the regression estimates. Pearson and Spearman correlational analyses indicated large positive correlations to support the construct validity between ROI, ENG ($r = .47$, $p < .01$), and CR ($r = .39$, $p < .01$), which directly supports our findings.

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3.5. Synthesis of findings with prior research

In sum, the three hypotheses are largely supported across the tests. Hybrid intelligence outranks single modes of generating ROIs (H1), especially for firms with ample market resources (H2) and works achieving results through behavioral mediators ENG and CR (H3). These findings corroborate and expand upon recent research. Vishwas et al. note the need to strive for a balance between the efficiency of AI and the contextual and creative value of human contributions that will lead to success in marketing applications [10]. Extending this idea, Petrescu and Krishen identify firm resources as a crucial moderator of hybrid systems and their ability to create superior returns [11]. Expanding upon the empirical groundwork of these relationships, Dellermann et al. present empirical evidence that human–AI collaboration facilitates more efficient processes and leads to improved output quality compared to existing human-only and AI-only counterparts [12]. In a related idea, Haleem et al. recognize that firm size is an important contextual factor concerning the level of expected returns of AI use [13]. Extending the argument, Turatti and Raji et al. observe that ROI outcomes are the direct result of engagement and conversion that was driven by personalization, while Oberoi and Wischhof used marketing case studies to identify that human–AI collaboration creates long-term brand loyalty as an outcome of combining AI's data-driven personalization with human ability to build relationships [14, 15]. By synthesizing these perspectives with statistical evidence and visual representations (Figures 1–3), this paper offers a rigorous, multifaceted demonstration that hybrid intelligence marketing is not only theoretically-based but also empirically-supported.

4. Discussion

4.1. AI system complexity and integration challenges

Statistical results in this study indicate that hybrid intelligence provides a much higher ROI than platforms either fully automated with AI or fully human modes, as demonstrated by the distributions illustrated in Figure 1, and confirmed by the ANOVA and Tukey post hoc tests that confirm the differences are statistically significant (H1). Przegalinska et al.explained that fully automatic AI systems can be very powerful and operationally effective, but often have excessive complexity and interconnectivity that only increase the cost of implementing and operational risk and ultimately the practical ROI for organizations as a whole. Hybrid intelligence is much more efficient and a human-centered design-based system that would imply a more sustainable balance between some efficiencies and still address the development and human-interface issues of an operational construct. The empirical contribution of this study further establishes that a hybridization of the interface, potentially possible by a human interface system of AI, vastly reduces system complexity and, in fact, acts to cover a wider array of development and human interface while still maintaining a sustainable and above-average ROI. In fact, the argument that governance and administrability, while utilizing hybrid intelligence, are not built into complete automation, will nonetheless provide real and sustainable economic returns to an organization's expertise and business arrangements.

4.2. Data privacy and transparency risks

The mediation analysis (Figure 3) indicates that engagement (ENG) and conversion rate (CR) were identified as positive mediator paths to ROI (H3). However, these paths also imply that improvement in ROI for hybrid modes occurs partly due (in our case) to improved engagement and

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trust in the customer experience. This indicates that, like Jiang et al., AI-based personalized experiences can certainly be quite efficient, but they can also pose several challenges (e.g., data privacy violations or algorithm black-box issues). While the interaction, hybrid intelligence allows brands to create better value by facilitating and/or mediating exchanges of timely, relevant, and immediate information rather than simply deploying an automated system or process. But hybrid intelligence represents compromises with engagement, but still trust in the experience. In the case of ROI measurement, it should very clearly account for 'governance' costs, like transparency, compliance, and oversight through policy mechanisms, that establish engagement that translates into higher-order returns. This fits with Jiang et al.'s call for transparency and the rewards of governance to help sustain long-term improvements in human-AI transactions [16].

4.3. Human–AI collaboration and governance mechanisms

Two-way ANOVAs were run with hybrid intelligence as the mode or dependent variable and firm size as a moderating variable (Figure 2), and show that firm size moderates the ROI advantage of hybrid intelligence (H2). Larger enterprises returned a significantly higher ROI compared to smaller brands in hybrid performance. This goes along with Mwamba and Nkosi’s (2023) suggestion that when human activities are explicitly organized, governed, and designed to facilitate hybrid intelligence, moving away from pure automation will lead to better performance [17]. Larger organizations have greater available resources and institutionalized structures to establish hybridized frameworks for maximizing ROI in terms of their efficiencies from deploying creative, analytical, and oversight roles. Smaller brands may not develop the governance capacities to even compete with larger brands or experience the returns. In line with Mwamba and Nkosi's (2023) argument, implementing governance mechanisms that allow for review and enhancements of AI systems by human supervision, especially for risk-taking and aesthetics, creates a control loop that reconciles organizational decisions with the normative expectations of investments into hybrid intelligence that positively contribute to valued and potentially lasting returns [18].

5. Research limitations and future prospects

5.1. Boundaries

This research has several limitations. First, the data, while extensive (~200,000 records, 16 variables), is confined to publicly accessible campaign-level data with some sample bias and is unable to tap into individual-level behavioral variables (e.g., time-based session logs, cross-platform activity), which may hamper the explanatory power of the ROI mechanisms. Second, the method of inquiry is primarily quantitative, with regression, ANOVA, and bootstrapped mediation being used for data analysis. As the authors Ng and Wakenshaw noted, without seeking to diminish the reliability of regression and ANOVA methods as forms of statistical inference, both of these approaches may not represent qualitative constructs—say, ethnographic insights, tacit knowledge, or the ethical and managerial dimensions of the human governance for a hybrid intelligence system—to provide the reader with a holistic understanding [19]. Third, the operationalization of variables (ROI, conversion rate, engagement score, firm size) is inevitably oversimplified, and may exclude variables capturing value at other stages of marketing (e.g., long-term loyalty or algorithm transparency) or direct/indirect governance costs. Thus, the findings may be limited in generalizability or applicability of the model in other cultural or industrial settings.

5.2. Prospects

Future inquiry might address these limitations in a variety of ways. First, approaches to data collection could aid, such as time-series or longer, multi-platform data (e.g., data collected at the firm-level) for greater evidence of the dynamics of ROI. Second, the scope of inquiry should be expanded to include the ability to extend comparison of hybrid intelligence and contributions beyond digital marketing (e.g., management, education, and public service sectors) — thus allowing further testing of hybrid intelligence models under various institutional constraints. According to Ng & Wakenshaw, human–AI collaboration is naturally sociotechnical, which suggests that it is important to research how cultural context, institutional governance systems, and organizational routines relate to various forms of hybrid intelligence performance across domains [19]. Third, construct variables could be included in the model, such as social perspectives of transparency, fairness of algorithms, or the human cost of governance, and alternatively, mixed method approaches, integrating elements of statistical modeling and qualitative inquiry, could present a method for generating both ecological validity and breadth and depth of conceptual knowledge supporting the framework more generally. Progressing in each of these areas can help convert hybrid intelligence research into a prescriptive and actionable strategy for managers [19].

6. Conclusion

In this research, hybrid intelligence is viewed as a strategic aspect of ROI in relation to AI automation, human creativity, and the hybrid collaboration of both in digital marketing. Through the analysis of nearly 200,000 real campaign records, a mixed-method quantitative framework was used, within which the ANOVA, regression, and bootstrap mediation methods were relevant. Hybrid collaboration provides a superior return on investment (ROI) compared to AI or humans in isolation, while also moderating the effect with firm size, as larger brands will naturally experience stronger hybrids. Engagement (ENG) and conversion rate (CR) provide significant mediation in the relationship from mode to ROI. The study tracks the operationalization of theoretical constructs through an ROI based framework in hybrid collaboration by using the Resource-Based View and Ambidexterity Theory. The study used a rare three-mode comparison and engaged all the complexity by using mediation and moderation analysis. By using firm size and governance factors to embed in the analysis, this clarifies its applicability to firms that are informed by hybrid tactical considerations and digital capabilities and quality data to be able to find that firms are able to weigh the efficiencies of automation against the creative value in collaboration informed by governance design. The study contributes to the theoretical advancement of research into hybrid intelligence in marketing strategy and marketing management, but also provides empirically grounded pathways to apply hybrid intelligence when marketing managers are required to incorporate hybrid tactical considerations back to strategic marketing management concerns, well beyond just marketing.

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