Exploring Human-AI Collaboration:
Resource Based View and Task Technology Fit Approach in Evaluating the Impact of Generative AI in the Workplace.

Abstract

This study presents an investigation into the interplay between artificial intelligence, human skills, and task characteristics, and their impact on organizational performance as well as worker's satisfaction. Applying the Resource-Based View and Task Technology Fit theories, we explored how generative AI hardcoded for collaboration, as both a firm resource and a capability, can enhance task execution across different dimensions - routine/creative tasks and easy/complex tasks. We conducted an experimental study involving the development of a marketing campaign with distinct subtasks reflecting these dimensions. Our findings show that firms can gain substantial benefits from integrating AI and that AI improves task outputs in automation, support, creation, and innovation. Our study also suggests a nuanced relationship between humans and AI in creative tasks with humans outperforming AI. The study highlights the value of upskilling and reskilling in AI, and proposes a strategic blend of AI and human creativity for optimal results. These findings have implications for understanding the role of AI in organizational tasks and formulating effective strategies for AI integration in business and beyond.

Keywords: automation of work, generative AI, human-AI collaboration, marketing, organizational performance

Introduction

The dynamics of the professional landscape are undergoing profound changes, as the advent of automation and artificial intelligence (AI), have begun to reshape conventional work models (Kaplan and Haenlein 2019) (Kellogg, Valentine, and Christin 2020) (Obschonka and Audretsch 2020) (Pachidi et al. 2021). Just a few years ago, experts predicted that automation and AI would primarily impact routine tasks and highly specialized professions. However, the emergence of generative AI has significantly challenged these assumptions (Dang et al. 2022).

In this study, we aim to evaluate how the collaboration between humans and AI is redefining the future of work, examining the associated benefits, challenges, and implications for both organizations and their workforce. The overarching objective of our research is to discern how AI integration is revolutionizing organizational perceptions of effective work and the subsequent impacts on productivity, and to unravel the synergies between human intellect and AI capabilities and highlight how their combined strengths could facilitate efficient and effective collaboration (Przegalinska et al. 2019; Sowa and Przegalinska 2020; Sowa et al. 2021) (Chalmers, MacKenzie, and Carter 2021) (Townsend and Hunt 2019).

Generative AI, a rapidly evolving subset of artificial intelligence, is characterized by its capacity to create unique and innovative content that mirrors human-like behavior (Ciechanowski et al. 2019, Dwivedi et al. 2023). These AI systems, trained on extensive data sets including text, images, or audio, leverage their training to produce original content. We aim to investigate generative AI within the context of human-AI collaboration, specifically focusing on virtual assistant usage, which is an AI chatbot technology capable of responding to users' queries by using natural language processing, natural language understanding, natural language response generation, and machine learning (Gkinko and Elbanna, 2023).

The very concept of human-AI collaboration in professional settings spans various fields, from data science and machine learning (Wang et al. 2019), to specialized applications like healthcare or logistics (Lai et al. 2021), managerial functions (Sowa et al. 2021) and organizational adoption (Uren and Edwards, 2023). The notion of human-AI collaboration embodies a spectrum of possibilities: from complementary and parallel work to synergistic interplay between human and machine intelligence, often referred to as the hybrid intelligence approach (Wiethof and Bittner 2022). This approach emphasizes the human-in-the-loop design model, which incorporates human intervention in the decision-making processes of AI systems, and also encompasses cooperative collaboration, a broader perspective on how humans and AI can jointly work towards shared objectives (Sowa, Przegalinska, and Ciechanowski 2021) (Shneiderman 2022).

In our study, we present an AI-based system designed for cooperative assistance in business tasks, particularly in the realm of marketing, such as the conceptualization and execution of an advertising campaign for a novel product[1]. We developed a text-based virtual assistant leveraging GPT 3.5 transformer technologies, incorporating techniques like hardcoding and few-shot learning to create a system with an enhanced focus on dialogue, differing from the prevalent answer-oriented design of current generative tools like ChatGPT. Our objective was to transition from a primarily answer-providing AI model to a more dialogue-oriented one that asks additional questions and provides shorter output per prompt. We employed the Resource-Based View) theory and Task Technology Fit model to examine how generative and collaborative AI can bolster human work across tasks of varying creativity and complexity, and how AI assistance can positively impact productivity, performance, and job satisfaction.

To the best of our knowledge, our study represents one of the first explorations into the effects of human-AI collaboration within an experimental setting. The paper is organized as follows: we first apply the Resource-Based View (RBV) and Task Technology Fit (TTF) in relation to generative AI, followed by a discussion on the roles of TTF and RBV in various tasks supported by generative AI. Next, we introduce the methodology and findings of our experiment including the results of AI-generated text analysis and conclude with a discussion on the implications of our research for businesses and society at large.

Resource-Based View

The Resource-Based View of a firm has emerged as a powerful theoretical framework that elucidates technology resources for organizations making strategic investments in a business environment (Wade and Hulland 2004). The fundamental notion that underpins RBV is the dependence of an organization's competitive standing on the unique resources it owns or controls (Barney 2001). These resources and capabilities can include tangible assets such as technology, equipment, and physical infrastructure, as well as intangible assets such as organizational culture, reputation, and knowledge (Barney 1991).

Within this perspective, not all resources hold equal value. Instead, the competitive advantage an organization can attain through resource utilization depends on the specific attributes of the resources themselves. In particular, resources that are valuable, scarce, difficult to imitate, and not readily substitutable can be a source of significant business value when leveraged effectively (Collis and Montgomery 2008).

Emerging technologies are considered a key organizational capability and are essential for firms to effectively utilize new and emerging technologies (Bharadwaj 2000). Due to the significant increase in data and computing power, AI has become an important technology that is expected to have a pivotal role in achieving business performance and gaining a competitive advantage for organizations (Davenport and Ronanki 2018). An AI capability refers to a firm's capacity to effectively choose, coordinate, and harness its dedicated AI resources for optimal results (Mikalef and Gupta 2021). AI capability has been studied in relationship to competitive performance (Mikalef et al. 2019), in the area of human resources (Chowdhury et al. 2023), integrated business analytics (Rana et al., 2022), customer relationship management (Chatterjee et al. 2021), big data analytics, circular economy and sustainable manufacturing (Bag et al. 2021).

In this research, we consider generative AI via the lens of the RBV framework. Generative AI, now a technological reality, can be seen as both a resource and a capability within the firm. As a resource, generative AI represents a technological asset that a firm can use to enhance its operational efficiency, improve decision-making, and drive innovation. The technology can automate routine tasks, generate new ideas, and provide data-driven insights, offering tangible benefits to firms that can effectively integrate and manage these systems. As a capability, generative AI reflects a firm's ability to leverage AI technology to create value and gain competitive advantage. This includes the firm's capacity to develop, implement, and manage AI systems, as well as its ability to adapt to AI-induced changes and integrate AI with other business processes.

In light of the preceding discourse concerning the integral components of an AI capability and the nascent literature addressing the business value of such technologies within an organizational context, the focal question becomes whether AI capability can foster business value and, if so, the mechanisms through which this can be accomplished. To fully leverage the potential of generative AI, firms need to develop AI-specific resources and capabilities. This can include AI-related knowledge and skills, data management capabilities, and an organizational culture that supports AI adoption and use (Davenport & Ronanki, 2018).

Within the framework of the Resource-Based View, generative AI stands out as a potentially transformative resource and capability for firms. Generative AI, by automating routine tasks, generating innovative ideas, and providing data-driven insights, embodies a technological asset that can enhance a firm's operational efficiency, decision-making, and innovative capacity (Mikalef et al., 2019; Davenport & Ronanki, 2018). However, the effective integration and management of these systems require a firm to develop AI-specific resources and capabilities. These can range from AI-related knowledge and skills to robust data management capabilities and an organizational culture that is conducive to AI adoption and use (Brynjolfsson & McAfee, 2014).

Given these considerations, possessing generative AI resources and capabilities could form a basis for competitive advantage. This aligns with the central tenets of RBV and reflects the emerging role of AI as a key strategic resource in the modern business environment. As such, we propose the following hypothesis:

H1: Firms that possess advanced generative AI resources and capabilities will have a competitive advantage over firms that do not.

The RBV also emphasizes the importance of human capital as a crucial resource for attaining competitive advantage (Barney, 2001). In the context of AI, this implies that employees need to possess the necessary skills and experience to effectively utilize AI technology (Davenport &

Ronanki, 2018). Employee familiarity with AI can contribute to a firm's ability to adopt, implement, and manage AI systems, as well as its capacity to adapt to changes induced by AI technology (Brynjolfsson & McAfee, 2014).

When employees are more experienced in AI, they are better able to leverage the technology's capabilities, thereby increasing operational efficiency, improving decision-making processes, and driving innovation (Mikalef et al., 2019). AI-experienced employees can also facilitate the integration of AI technology with other business processes, which is crucial for maximizing the value derived from AI investments (Davenport & Ronanki, 2018).

Therefore, with the growing importance of human capital in the age of AI, we propose that firms with AI-related knowledge and skills will benefit in today's business landscape. More formally:

H2: Firms with employees more experienced in AI will have a competitive advantage over firms that do not.

Task Technology Fit

As artificial intelligence becomes increasingly intertwined with our everyday lives, the collaboration between humans and this technology grows ever more significant. This partnership can manifest in various ways, including humans cooperating with AI assistants or AI systems assisting humans to complete tasks. The Task Technology Fit theory provides a model that details how the characteristics of a task, paired with the attributes of the technology used to perform it, can influence individual performance. This theory has proven invaluable as a diagnostic tool for assessing whether a technology aligns with user needs in the workplace (Goodhue & Thompson, 1995).

TTF offers a framework for evaluating the suitability of a technology for a specific task or job (Goodhue & Thompson, 1995). It proposes that the efficiency of technology hinges on its compatibility with the task requirements, user attributes, and organizational context. The closer the match between the technology and the task, the higher the potential benefits. When applied to AI, the TTF model can analyze how well AI technologies align with specific tasks or job functions. By gauging the compatibility between task demands and the capabilities of the AI system, organizations can determine whether AI can enhance productivity, performance, and job satisfaction. The efficacy of AI is dictated by how well it meets the task requirements. Certain tasks demand high levels of accuracy, speed, and efficiency, while others may require more creativity, social intelligence, and adaptability. This evaluation helps to identify which tasks are best suited for AI automation and which ones benefit more from human intelligence and ingenuity.

Task characteristics refer to the nature and structure of a task. For instance, a highly structured, routine task is likely a good fit for an automated, efficient technology. Conversely, a task requiring creativity may better suit a flexible, adaptable technology. Therefore, systems with high generative capacity may stimulate individuals to produce original content (Avital & Te'eni, 2009). Given the variety of tasks and technologies within an organization, we expect that AI adoption in the workplace can be shaped by these task and technology characteristics.

The creative-routine and easy-difficult dichotomy of tasks is pivotal in discerning how AI can contribute value in different business scenarios. We identified the four value-generation avenues of AI capability inspired by Mikalef et al. (2019) - Automation, Decision Support, Creation, and Innovation.

INSERT TABLE I ABOUT HERE

Automation generally corresponds to routine and easy tasks. These repetitive tasks follow a specific set of rules or procedures, making them suitable for AI automation, which can save time and resources while reducing potential human errors.

H3a: Firms utilizing generative AI for automation tasks will perform these tasks more effectively than firms that do not.

Decision Support can cover both easy and difficult tasks, proving particularly crucial for complex decisions requiring intricate analysis or judgment. AI can facilitate these tasks by processing vast quantities of data and offering insights difficult for humans to discern.

H3b: Firms employing generative AI for decision support tasks will perform these tasks more effectively than firms that do not.

Creation straddles both the creative aspects of the dichotomy. AI can facilitate the generation of new and innovative ideas, concepts, or solutions, which requires a certain degree of creativity. This could involve using generative AI systems to produce new concepts in design, art, product development, or strategic planning.

H3c: Firms that integrate generative AI in their creative tasks will perform these tasks more effectively than firms that do not.

Innovation is linked with creative and difficult tasks. AI can generate fresh ideas or solutions, analyze complex patterns, or simulate potential scenarios, thereby enhancing innovation by providing novel perspectives and reducing decision-making risk.

H3d: Firms that leverage generative AI for innovation tasks will perform these tasks more effectively than firms that do not.

Methodology

<u>Task</u>

The aim of this research is to explore the adoption and applicability of generative AI in the workplace, with particular attention given to how different task characteristics might influence its effectiveness. These task characteristics are delineated based on two dichotomies: the complexity of the task (simple vs complex) and the degree of creativity required (routine vs creative).

For this purpose, we evaluate how AI can be employed in the development of a marketing campaign for an innovative product. Marketing is considered one of the areas where AI is particularly beneficial (Mikalef et al. 2019). Participants were asked to get into the shoes of a marketer working for an agency, whose customer (a manufacturer of innovative functional chewing gum) was in need of a marketing campaign. We then asked participants to perform four tasks that are commonly associated with marketing jobs - come up with a product name, run a competitor's analysis, describe a marketing persona for the new product and write an advertisement based on results from tasks done thus far. Explanatory materials were provided to all participants. With the process being broken down into several subtasks, each task represented a different quadrant othe Task Technology Fit model based on complexity and creativity:

INSERT TABLE II ABOUT HERE

Participants

The participants constituted a diverse group of students and professionals. Among the participants, we can distinguish graduate management students who recently graduated with an undergraduate degree in business disciplines such as accounting, finance, marketing, or management. In that group, we also have three students who classified themselves as undergraduate, but attended an elective course on the graduate level. The second group are Executive MBA and postgraduate program students with significant professional experience from their prior positions in the business world.

Participants were recruited from a large, prestigious business school in Poland, and were randomly assigned to one of the two established conditions. The experimental treatment was administered in person, including the instructions on how to proceed, to avoid experimenter effects and to ensure that all participants received the same information. Participants were not remunerated for their work.

Sample included 94 participants, 90 of which provided demographic information. Participants primarily comprised students at graduate, executive MBA or postgraduate levels. Out of those $N = 89$ provided responses for the familiarity with Generative AI questions. The age distribution of participants was diversified, with the slight majority (34%) falling within the 35 - 44 age category. Other age groups included 18 - 24 (24%), 25 - 34 (22%), 45 - 54 (17%), and 55+ (2%). In terms of gender, the marginal majority of participants identified as male (54%), followed by female (44%) and other (1%).

With respect to occupational status, the largest portion of participants were either employed full time (43%) or concurrently employed full time and studying (38%), while others were, graduate students (11%), undergraduate students (6%), or working undergraduate students (2%).

The diversity of fields in which the participants worked or studied was noteworthy. The highest proportion of participants hailed from Management (58%), followed by Information Technologies (IT) (13%), Economics and finance (11%), Marketing (6%), Engineering (4%), and lesser percentages in Health, Legal, Political Sciences, and Psychology fields. Among participants currently employed (83%), a significant proportion occupied Upper management positions (36%), followed by Mid-level (24%), Executive/ C-level (17%), and Self-employed (7%).

This robust participant representation, encompassing a broad range of ages, genders, educational backgrounds, professional positions, and fields of study, was integral to the design of our experiment.

Generative bot

The bot developed within this research project is a virtual assistant designed to facilitate human-AI collaboration in the workplace. Its primary functionality is to support human workers, providing real-time interaction and complementary capabilities designed for marketing tasks. The bot is based on GPT 3-5 engine developed by OpenAI. It was first set up on Streamlit, a platform that allows developers to create interactive web apps for machine learning and data science projects. This provided a user-friendly, accessible interface, which was important in facilitating meaningful interaction between the bot and its human users. The limitation of Streamlit was related to the fact that the users needed to save their answers which added more burdens to task solving. The bot was subsequently hosted on PythonAnywhere, where all answers were saved automatically. Let us add that PythonAnywhere is an online platform that allows Python applications to be run on servers in the cloud, increasing the bot accessibility and further enhancing its utility inwork environment.

This bot's design took a novel approach, going beyond the traditional assistant model that simply responds to queries. Instead, it was coded for collaboration with human users. In addition to providing answers and unless the prompt of the user was detailed and diligent, where all answers were saved automatically. This iterative dialogue promotes critical thinking and decision-making processes, helping both the bot and the human user to arrive at the final task solution together. Examples of shared tasks are provided in the appendix.

Procedure

The experiment was conducted in person. During the experiment, the participants answered pre-study survey questions including demographics, and Generative AI familiarity questions. Participants' familiarity with Generative AI was evaluated by the question “Have you used generative AI such as Lensa, Dalle-2, BERT or ChatGPT?”. They classified their level of familiarity as Not at all (coded as No Familiarity), A little bit (Coded as Moderate Familiarity) or A lot (Significant Familiarity). In the second part, the participants were randomly assigned to work either individually or with the assistance of our pre-trained GPT 3.5-based virtual assistant (respectively, group Generative AI and No Collaborator). There were approximately equal numbers of participants in two groups: $n = 43$ in the Generative AI and $n = 51$ in the No Collaborator group (χ^2 $(1) = 0.72$, $p = 0.4$). The participants varied regarding their levels of experience in product launch campaigns. Majority of the participants from Executive MBA groups were experienced and had seniority in management related tasks, including marketing. Graduate groups had experience with marketing, but often limited to Business School courses setting. The participants completed the tasks within a set time frame (45 mins). On average participants completed study within 19.5 min ($SD = 10.8$ min).

The quality of the output for each task was evaluated by a panel of independent judges. Three marketing experts - two university professors from Poland and the United States and one professional marketer working for a large company in Poland assessed the quality of proposed marketing campaigns based on accuracy and creativity. The quality of the tasks completion was assessed by asking judges to rate participants' responses for the tasks on the scale from 1 to 5. For product name tasks judges were asked to rate participants' answers in the following aspects: originality of the name, shortness and simplicity, resonating with the features of the product, and revealing benefits of the product. For competitive analysis judges evaluated depth of the analysis and variety of the analysis (presenting direct and indirect competitors as well as substitutes). For the text-based ad judges rated to what extent is the ad fitting the persona, to what extent is the ad fitting the medium, and to what extent is the ad attention-drawing and successful in increasing the awareness of the brand. Lastly, persona evaluation included aspects such as how detailed is the marketing persona created, how does the persona fit the product, and to what extent is the presented persona a solid basis for communication activities. Cronbach's alpha was calculated to measure the reliability of the created scales. Cronbach's alpha for the quality of product name scale was 0.84, competitive analysis 0.98, text-based ad 0.97 and persona 0.98, which indicates that the proposed scales are reliable. To measure the quality of each task completion the average of the judges ratings of each aspect of the task was taken. The methodology also included qualitative review of experiment output by the judges. The results of the analyses revealed an average inter-judge reliability of 0.464 (Krippendorff 2011). This value of Krippendorff's Alpha indicates a moderate level of agreement among the judges. Furthermore, the range of Krippendorff's Alpha across different assessments was found to be 0.717, which indicates a substantial variation in the levels of agreement for different assessments. This is also supported by the calculated standard deviation of 0.191, which suggests that the reliability scores were dispersed around the mean.

In interpreting these results, it is important to consider that while an average Krippendorff's Alpha of 0.464 suggests a moderate agreement among judges, the substantial range and standard deviation indicate variability in the consistency of the ratings. This could suggest that, in some instances, the judges were more aligned in their assessments, whereas in others, there was greater divergence. Therefore, it is essential to consider both the average reliability and the variability in reliability scores when evaluating the overall inter-judge agreement in this study. The moderate level of agreement among judges might also be attributed to the inherent complexity and creativity involved in the tasks assessed. For instance, one of the primary tasks required participants to create a new product description, in this case, a neuroactive chewing gum. Participants were expected to come up with a product name, perform a competitor's analysis, describe the customer persona, and create an advertisement based on the persona and product description. In evaluating creative tasks like these, judges may find it difficult to reach a consensus due to the subjective nature of creativity and the diverse approaches that participants may take. Moreover, judges might have different perspectives on what constitutes an effective competitor analysis, customer persona, or advertisement. The interplay between creativity and subjectivity in the tasks could explain the moderate agreement levels among the judges. As such, it is essential for future studies to consider the nature of tasks and the criteria for evaluation to ensure more consistent and objective assessments.

Results

The data preprocessing was done with the use of standard Python libraries (pandas, numpy, datetime). Statistical analysis and visualization were performed using RStudio 2023.03 and such libraries as dplyr, tidyverse, lsr, stats, ggplot2 and ggpubr.

To test hypotheses requiring comparison of two independent groups, Independent t-test or Welch's t-test were selected. The independent t-test was used when variances of the two groups being compared were equal as suggested by Levene’s test (H3b, H3d). More robust Welch's t-test was used when the assumption of equal variances was violated for traditional t test (H3c). Similarly, a robust alternative to the traditional one-way ANOVA for three groups, Welch one-way ANOVA, was selected to test H2 due to the unequal variances and group sizes. Bartlett’s test was performed to determine if the variances are equal.

To test our first hypothesis, we conducted the Welch Two Sample t-test to examine the difference in the quality of task output between participants in the group interacting with Generative AI ($M = 3.27$, $SD = 0.8$, $n = 43$) and the group with No Collaborator ($M = 2.25$, $SD = 0.54$, $n = 51$) (Figure 1). The t-test revealed a significant difference in quality between the groups ($t(71.26) = 7.17$, $p < 0.001$). Additionally, the effect size was calculated using Cohen's d, which indicated a large effect ($d = 1.53$). Thus, H1 is supported.

INSERT FIGURE1 ABOUT HERE

To test the second hypothesis (H2), we employed Welch one-way ANOVA to investigate the differences in the quality of the tasks between the groups with no familiarity, moderate familiarity, significant familiarity with Generative AI. We removed 5 cases due to the missing responses to the question of familiarity with Generative AI. There were significant differences in the quality of tasks depending on the prior familiarity with Generative AI for persona ideation ($F(2, 86) = 5.18$, $p = 0.008$, $\eta 2 = 0.11$), competitive analysis ($F(2, 86) = 4.77$, $p = 0.019$, $\eta 2 = 0.1$), text-based ad ($F(2, 86) = 3.77$, $p = 0.027$, $\eta 2 = 0.08$) but not for the product name task. Additionally, the effect size was calculated using the eta squared ($\eta 2$) measure. The effect size was medium for product name and large for competitive analysis and persona ideation tasks. The medium effect size indicates that there is a moderate, but still noticeable, relationship between the familiarity with Generative AI technology and the quality of the text-based ad. The large effect size for competitive analysis and persona ideation tasks suggests a substantial and significant relationship between the variables familiarity with technology and quality. The effect is substantial enough to be easily detectable and likely to have practical importance.

Tukey HSD post hoc test adjusted for multiple comparisons revealed the better quality of three tasks for participants that were not familiar with Generative AI and had significant familiarity (Table III). Participants with a significant familiarity with Generative AI compared to those with no familiarity had a better quality of persona ideation ($M = 3.23$, $SD = 1.13$ vs $M = 1.95$, $SD = 0.75$, $p = 0.0053$), competitive analysis ($M = 3.31$, $SD = 1.18$ vs $M = 1.99$, $SD = 0.84$, $p = 0.0076$) and text-based ad ($M = 3.12$, $SD = 0.96$ vs $M = 2.1$, $SD = 0.79$, $p = 0.0219$) tasks. The group that used Generative AI moderately was not different in the quality of the tasks from the other two groups ($p>0.05$).

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To test hypothesis H3a we employed Welch two sample t-test to investigate the disparity in the quality of the persona ideation task between the group with Generative AI ($M = 3.1$, $SD = 1.04$) and the group without a collaborator ($M = 2.09$, $SD = 0.75$) (Table IV). The t-test yielded a significant difference in the quality of the task between the groups ($t(74.68) = 5.3$, $p < 0.001$). The effect size measure indicated a large effect size ($d = 1.13$).

INSERT TABLE IV ABOUT HERE

To test hypothesis H3b, Independent sample t-test was selected to compare the quality of the competitive analysis task in the Generative AI ($M = 3.33$, $SD = 1.06$) and No Collaborator group ($M = 2.06$, $SD = 0.76$) (Table IV). Group participating in the experiment with the Generative AI compared to the group with No Collaborator had a significantly better quality of competitive analysis task ($t(92) = 6.72$, $p < 0.001$). The effect size was large ($d = 1.39$).

To test hypothesis H3c we employed Welch two sample t-test to investigate the quality of the text-based ad task in the Generative AI ($M = 3.17$, $SD = 0.92$) and No Collaborator group ($M = 2.05$, $SD = 0.63$) (Table IV). Group participating in the experiment with the Generative AI compared to the group with No Collaborator had significantly higher quality of text-based ad task ($t (92) = 6.72$, $p < 0.001$). The effect size was large ($d = 1.43$).

Similarly to the previous tasks, to test hypothesis H3d, we used an Independent sample t-test to compare the quality of performance in product naming tasks in Generative AI ($M = 3.51$, $SD = 0.63$) and No Collaborator ($M = 2.8$, $SD = 0.69$) groups (Table IV). Participants collaborating with Generative AI compared to the group with No Collaborator had significantly higher quality of product naming task ($t (92) = 5.18$, $p < 0.001$). Effect size measure indicated a large effect size ($d = 1.07$).

Text analytics results

In addition, we analyzed the conversations between humans and AI based on a set of 74 logs produced during the experiments, since we were able to save conversations for only one group interacting with the chatbot (the group consisted of 10 persons). Only conversations that had at least eight messages (four from a human and four from AI) were included in the analysis, in this way 3 users were removed. We applied this approach, because we assumed that less than 4 messages from the user and 4 from the chatbot would not comprise a real-like conversation. Five linguistic metrics were computed for each message, including sentiment, Flesch-Kincaid readability (Flesch 2007), Gunning Fog index (Gunning 1969), lexical diversity (McCarthy 2005), average sentence length, and vocabulary level. In the analysis, the vocabulary level of the texts was computed using a bag-of-words model (Sebastiani 2002).

These tests were conducted to compare the fundamental linguistic differences between messages produced by humans and those produced by AI. The purpose was to scrutinize AI's capabilities in various aspects of communication, evaluate the quality of its output compared to human users, and identify areas where the AI models excel or needs improvement. The identified metrics, such as sentiment and vocabulary level, help evaluate the emotive language use and sophistication of language respectively. Similarly, sentence length and readability scores can indicate complexity and understandability of the messages. Lexical diversity is a measure of the range of vocabulary used, revealing the depth of language. Gunning Fog index aids in understanding the readability based on sentence length and complexity of words used.

The Mann-Whitney U test revealed statistically significant differences between human users and the AI chatbot in sentiment ($U = 1085$, $p < .001$, Cliff's Delta = -0.604), Gunning Fog index ($U = 2207.5$, $p = .042$, Cliff's Delta = -0.194), lexical diversity ($U = 3670$, $p < .001$, Cliff's Delta = 0.34), average sentence length ($U = 1448$, $p < .001$, Cliff's Delta = -0.471), and vocabulary level ($U = 1141$, $p < .001$, Cliff's Delta = -0.583). However, there was no statistically significant difference in Flesch-Kincaid readability scores ($U = 2258.5$, $p = .066$, Cliff's Delta = -0.175). The AI chatbot had a higher mean sentiment ($M = 0.678$, $SD = 0.240$) compared to human users ($M = 0.290$, $SD = 0.343$), as well as higher Gunning Fog index ($M = 10.07$, $SD = 3.07$), average sentence length ($M = 14.01$, $SD = 4.87$), and vocabulary level ($M = 40.80$, $SD = 34.49$). Conversely, human users had a higher mean lexical diversity ($M = 0.947$, $SD = 0.080$) than the AI chatbot ($M = 0.883$, $SD = 0.118$) (Figure 2). The effect sizes, as measured by Cliff's Delta, indicated a large effect size for sentiment and vocabulary level, a medium effect size for average sentence length, a small effect size for lexical diversity, and negligible effect sizes for Flesch-Kincaid readability and Gunning Fog index.

INSERT FIGURE 2 ABOUT HERE

In examining the disparities between human and AI-created messages, we discovered several implications for industries, particularly in marketing applications. The AI displayed an elevated sentiment score, indicative of its propensity for using more affirmative language, which customers could interpret as polite and engaging—a critical aspect in fostering positive consumer interactions. Furthermore, the AI's superior language complexity, as revealed by the

Gunning Fog index, average sentence length, and vocabulary level, insinuates its proficiency in conveying intricate and technical information, a valuable asset in business-to-business marketing or when elucidating complex products.

However, the AI's reduced lexical diversity suggests potential limitations in the scope and inventiveness of its responses. In stark contrast, the higher lexical diversity exhibited by humans testifies to their potential for more innovative and dynamic communication—a crucial element in marketing for capturing audience attention and distinguishing products or services. Consequently, a potent strategy could be the blending of AI's proficiency in managing intricate details with the creative prowess inherent in human marketers. For instance, an AI might engage in initial customer interactions and deliver detailed product information, while human marketers might handle tasks demanding creativity and personalization.

Additionally, discerning the linguistic disparities between human and AI communication can empower businesses in refining AI systems to align more closely with their marketing goals. For instance, if a business is keen to ensure that their AI chatbot can interact with customers in a more personalized and inventive manner, they could focus on enhancing the chatbot's lexical diversity. Similarly, if the goal is efficient delivery of technical information, maintaining high levels of language complexity in the AI may prove beneficial.

Contributions

The significance of this study lies in its innovative exploration and integration of two distinct theoretical constructs, the Resource-Based View and the Task Technology Fit model, in the specific context of generative Artificial Intelligence. Furthermore, it extends the existing scholarly conversation by scrutinizing lexical differences between humans and AI in business communication.

Traditionally, the Resource-Based View and the Task Technology Fit have been employed separately in different fields, with RBV being rooted in strategic management, primarily focusing on the firm's internal resources, and TTF, originating from information systems research, dealing with the alignment between the capabilities of a technology and the demands of a specific task. This research transcends these boundaries, presenting a pioneering investigation of how these two concepts might intersect and coalesce in the realm of generative AI. By drawing on the principles of RBV and TTF, the research offers a unique analytical lens to examine how AI can be optimized as a valuable resource, and how it can best align with specific tasks, thus paving the way for novel insights in both fields.

Moreover, this study enriches the existing research body by examining human-AI collaboration in an experimental context. By venturing into experimental research focused not on the interaction itself, but different modalities of collaboration on routine and creative tasks, this paper makes a significant leap towards understanding the causality and underlying mechanisms of human-AI collaboration. This helps to demystify the processes and dynamics of collaboration, shedding light on optimal ways to design and deploy AI systems for human engagement.

In addition, the combined RBV-TTF approach can inform business leaders and AI developers about how to leverage AI's capabilities to maximize organizational resources and optimize task execution. At the same time, experimental insights into human-AI collaboration can guide the design of more intuitive, efficient, and effective AI systems, fostering more seamless integration of AI into our workplaces, homes, and lives.

We also established a task classification system based on a routine/creative and easy/complex dichotomy. This classification system aimed to identify areas where AI could provide significant benefit. Through this, we were able to better understand the nuances of Task Technology Fit in the context of AI. Our findings show that firms can gain a competitive advantage through the use of AI. This outcome can be linked to the Resource-Based View, which posits that valuable, rare, inimitable, and non-substitutable resources within a firm can contribute to sustained competitive advantage. AI, as a transformative technology, fits these criteria well. When harnessed effectively, AI can automate routine tasks, augment decision-making processes, drive innovative practices, and enhance marketing strategies, thereby generating substantial business value and competitive advantage.

Our research results also confirmed that employees with more advanced AI skills performed better across all tasks. This correlation highlights the integral role of AI competency in optimizing the use of AI resources within an organization. Upskilling and reskilling in AI have become not just beneficial but necessary steps for firms seeking to fully leverage the power of AI. This finding suggests that firms investing in their workforce's AI skills gain a competitive advantage.

However, we uncovered an intriguing outlier within our results: the creative task of product name generation. Despite the demonstrated link between AI proficiency and task performance, we found no noticeable difference in output quality tied to prior AI experience for this particular task. This suggests that while AI has vast potential to augment and streamline tasks, its impact on purely creative tasks may be less pronounced. It could be that human creativity, as of yet, is a unique capability not entirely replicable or augmentable by AI. Alternatively, current AI technology might still lack the full capability to enhance creative processes such as inventing a product name. The result underscores that while AI is a potent tool in many areas, the human element – particularly human creativity – remains essential in certain aspects of work. The blend of human creativity and AI's computatinal power could offer the best solution for such tasks. This interesting finding points to the need for further investigation into how AI can be better designed and used to augment human creativity.

As for the task classifications – automation, support, creation, and innovation (H3), our findings highlighted that AI was instrumental in improving the output across all these task types. The diverse applications of AI, from the automation of routine procedures to the augmentation of complex decision-making, and from the creative tasks to the innovation-oriented ones, serve to demonstrate the extensive potential of AI. The positive impacts of AI were observed irrespective of the task's complexity or the level of creativity required, further emphasizing the technology's transformative potential.

Finally, upon evaluating the disparities between AI and human-crafted messages, we identified several potential implications for businesses, particularly within the marketing realm. The AI's propensity for positive language and its ability to convey complex information can be invaluable in customer engagement and B2B communications. However, its limited lexical diversity could hamper its creativity, where humans excel. As such, a blend of AI's detail handling and human creativity could be a potent strategy. Recognizing these linguistic disparities also offers businesses an opportunity to refine their AI systems to better align with their marketing objectives.

Limitations

While this research provides valuable insights into the potential of human-AI collaboration in the workplace, there are several limitations that should be acknowledged. First of all, limited scope, as the study primarily focuses on generative AI and its applications in business-related tasks. It does not comprehensively address other subsets of AI or their potential impact on the workplace. Secondly - generalizability, as the findings may not be generalizable to all industries or occupations. One of the crucial limitations is related to technological advancements - as AI and other technologies continue to evolve rapidly, the findings of this research focused on the usage of GPT-3.5 engine may quickly become outdated. Another component is subjectivity in human-AI collaboration. The study utilizes the RBV and TTF models to evaluate productivity and performance benefits.. However, these outcomes may be influenced by individual differences and subjective perceptions of human-AI collaboration, which may not be adequately captured by the the RBV and TTF model. Finally, experimental design limitations related to the fact that this study relies on self-report measures, which could introduce biases or limit the external validity of the findings. Additionally, the study may not account for long-term effects of human-AI collaboration on employee performance and well-being. This, on the other hand, could be well captured by another longitudinal study.

It is also important to acknowledge that this study employed a quasi-experimental design. To establish a stronger causal relationship and confirm these findings, further experimentation would be required. Specifically, conducting an experiment with participants who are naive to technology and training them to use Generative AI tools could provide more certainty regarding the impact of AI on task completion and performance.

Conclusion

In summary, the study's findings suggest that the Generative AI group outperformed the control group in quality of all tasks completion. Familiarity with Generative AI was linked to better quality of tasks with a large effect size for the persona ideation and competitors tasks and a medium effect size for the text-based ad generation task. No effect was observed for the product name task. The results emphasize the potential benefits of familiarity with AI in improving task performance. However, further experimental research would be valuable to establish a more definitive understanding of these relationships.

The results indicate that the quality of all tasks, including text based ad generation, product name, persona ideation, and competitors analysis tasks, was better for the Generative AI group compared to the no collaborator group as assessed by the independent judges. This suggests that using AI technologies had a positive impact on task performance, regardless of the specific task being performed.

Furthermore, the findings suggest that familiarity with Generative AI can potentially help improve the persona ideation and competitors analysis tasks. This implies that when individuals are more familiar with AI technologies, they are likely to perform better in tasks related to creating personas and analyzing competitors. The effect size was reported as large for these tasks, indicating a substantial impact.

However, it should be noted that the effect size for the text-based ad task was medium, suggesting that while the AI group still performed better, the improvement may not be as pronounced as in the other tasks. This suggests that familiarity with AI may have a lesser influence on improving performance in this task.

Additionally, the results indicate that improving familiarity with AI technologies is not linked to an improvement in the product name task. This suggests that the use of AI may not have a significant impact on the quality of name generation.
The practical implication of these findings for marketing specialists is noteworthy. It suggests that incorporating AI technologies and making individuals more familiar with them can be especially beneficial for improving performance in persona ideation and competitors analysis tasks. This highlights the potential of AI as a valuable tool in these specific areas of marketing.

This study has revealed insights into the role of Generative AI as both a resource and a capability within modern firms, based on the Resource-Based View and Task Technology Fit perspectives. Our findings suggest that the utilization of AI can be a strong factor in establishing a competitive advantage for businesses. This research also yielded a classification system for tasks in which AI could offer benefits. By employing a scale of routine/creative and easy/complex tasks, we were able to discern the effectiveness of AI in automating routine tasks, supporting decision-making processes, aiding in creation, and driving innovation.

Additionally, we determined that employee expertise in AI contributes to better performance across a variety of tasks. The only exception was observed in highly creative tasks, such as product name creation, where prior AI experience did not significantly impact the output. This could suggest the irreplaceable nature of human creativity in certain contexts, despite the sophistication of AI technologies.

The lexical analysis of human-AI communication revealed that the AI's tendency towards positive language and its capability to relay intricate details can enhance customer engagement and B2B communications. However, the limitations in its lexical diversity could inhibit its capacity for creativity, an area where humans remain superior. Therefore, a harmonious blend of AI's efficiency and human creativity could be a powerful strategy in supporting business-related goals.

Figures and Tables

Table I. Task classification and value-generation avenues of generative AI capability

Task	**Simple**	**Complex**
Routine	Automation	Decision Support
Creative	Creation	Innovation

Table II. Task classification based on complexity and creativity

Task	**Simple**	**Complex**
Routine	Automation task: Persona Ideation	Decision Support Task: Competitive Analysis
Creative	Creation task: Text-based Ad	Innovation task: Product Naming

Table III. Descriptive Statistics for Quality of Tasks Completed by Participants with No familiarity Moderate familiarity, Significant familiarity with Generative AI.

Familiarity with Generative AI		**Persona Ideation**			**Competitive Analysis**			**Text-based Ad**			**Product Naming**		
	N	***M***	***SD***	***F***	***M***	***SD***	***F***	***M***	***SD***	***F***	***M***	***SD***	***F***
No familiarity	12	1.95	0.75	5.18**	1.99	0.84	4.77*	2.10	0.79	3.77*	2.89	0.56	0.44
Moderate familiarity	64	2.54	1.01		2.65	1.08		2.53	0.96		3.14	0.79	
Significant familiarity	13	3.23	1.13		3.31	1.18		3.12	0.96		3.31	0.63	

Note: N = 89, 5 cases deleted due to missingness

*: p value < 0.05, **: p value < 0.01

Table IV. Descriptive Statistics for Quality of Tasks Completed by Participants with No familiarity Moderate familiarity, Significant familiarity with Generative AI.

		Persona Ideation			Competitive Analysis			Text-based Ad			Product Naming		
Group	***N***	***M***	***SD***	***t***	***M***	***SD***	***t***	***M***	***SD***	***t***	***M***	***SD***	***t***
Generative AI	43	3.10	1.04	5.3***	3.33	1.06	6.72***	3.17	0.92	6.72***	3.51	0.63	5.18***
No Collaborator	51	2.09	0.75		2.06	0.76		2.05	0.63		2.80	0.68	

Note: ***: p value < 0.001

Figure 1. Comparison of Quality of Completed Tasks for Group with Generative AI Collaborator and Without. *Group participating in the experiment with the chatbot had significantly better average quality of tasks compared to the group without the collaborator (p < 0.001).*

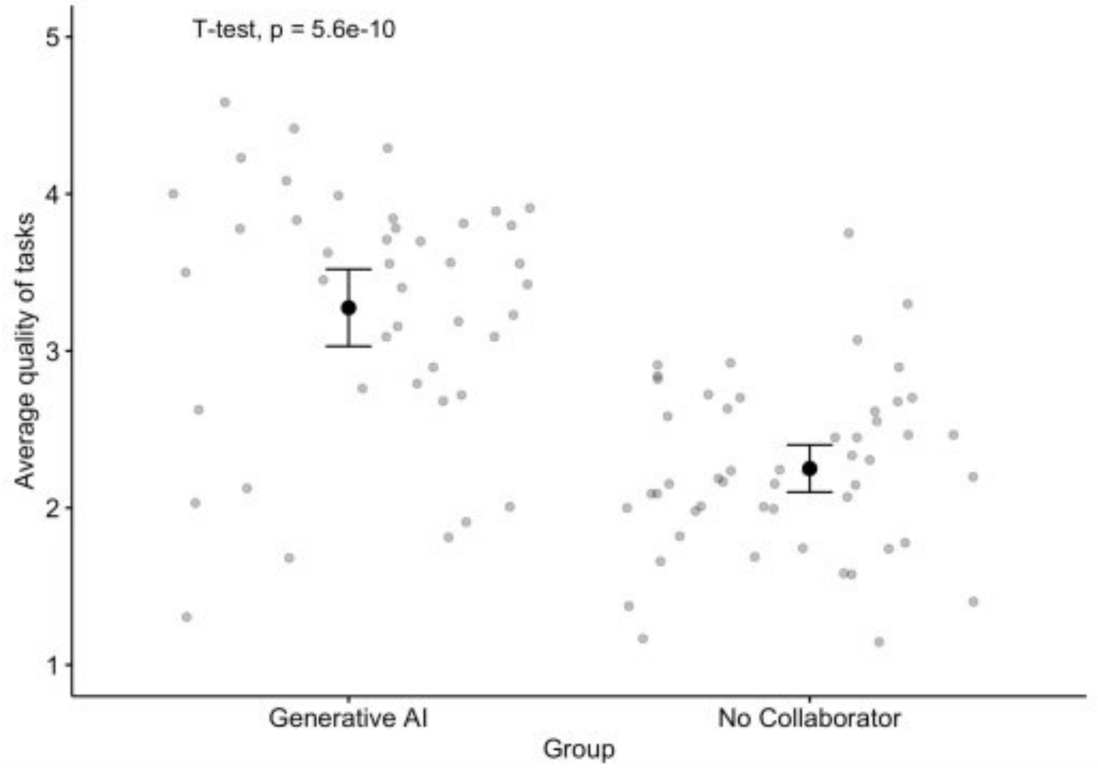
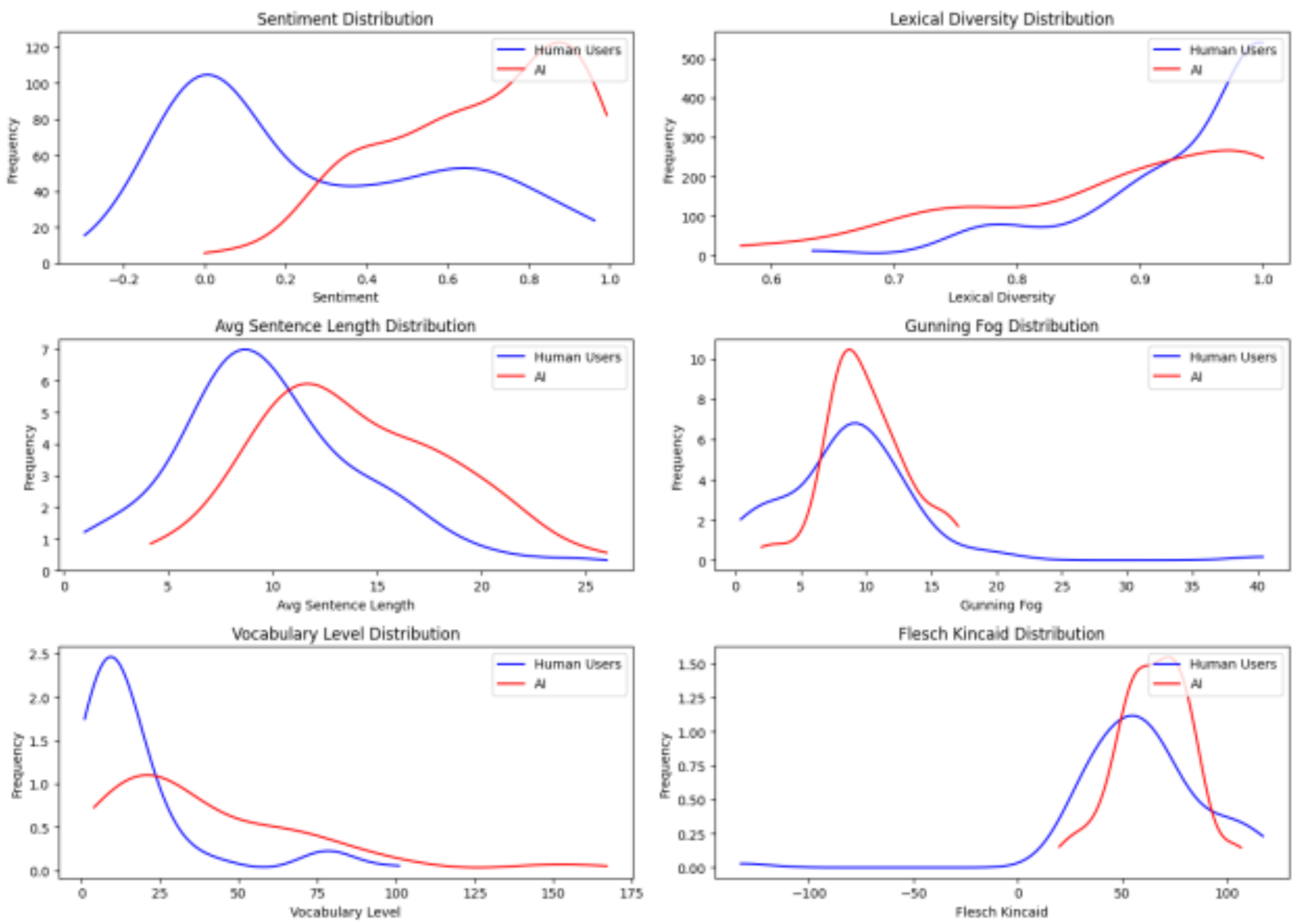


Figure 2. A set of subplots presenting the studied text metrics.



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Appendix A-1 Survey Items - pre-experiment survey

1. What is your gender?
    a. Male
    b. Female
    c. Other
2. What is your age?
    a. 18-24
    b. 25-34
    c. 35-44
    d. 45-54
    e. 55 or older
3. What is your employment status? You can select several options from the list below.
    a. Employed full time
    b. Employed part time
    c. Unemployed
    d. Graduate student
    e. Undergraduate student
4. What is your major?
5. What is your native language?
6. What language(s) do you speak at home?
7. Have you used a virtual assistant such as Siri, Alexa, Cortana, Bixby or similar?
    a. Not at all
    b. A little bit
    c. A lot
8. Have you used generative AI such as Lensa, Dalle-2, BERT or ChatGPT?
    a. Not at all
    b. A little bit
    c. A lot
9. How familiar are you with AI? Please provide the answers to the statements below: (answers: strongly disagree/disagree/neither agree or disagree/agree/strongly agree)
    a. I know a lot about generative AI such as Bard or ChatGPT
    b. I am very good at generating prompts when working with generative AI
    c. I have extensive knowledge about AI in general.
10. The tasks below are usually used to create and launch new products. How familiar are you with these tasks?
    (answers: not familiar at all/slightly familiar/moderately familiar/very familiar/extremely familiar)
    a. Competitive analysis
    b. Product ad development
    c. Persona ideation
    d. Product name generation
11. If you were to perform these tasks, how easy or difficult would these tasks be for you? (very difficult/somewhat difficult/neither easy or difficult/somewhat easy/very easy)
    a. Competitive analysis
    b. Product ad development
    c. Persona ideation
    d. Product name generation

12. Please evaluate the tasks below. In your opinion, are they routine or creative? (very routine/somewhat routine/neither routine or creative/somewhat creative/very creative)
    a. Competitive analysis
    b. Product ad development
    c. Persona ideation
    d. Product name generation

Appendix A-2 Survey Items - post-experiment survey

1. On a scale from 1 to 10, how are you feeling today?
   (answer: scale 1 not good - 10 excellent)
2. How focused were you while working on the task?
   (answers: strongly disagree/disagree/neither agree or disagree/agree/strongly agree)
   a. I was so involved working on the tasks that I ignored everything around me
   b. When I worked on the tasks, I lost the track of time
   c. When working on the tasks I was absorbed with the task
3. How much have you enjoyed the task?
   (answers: strongly disagree/disagree/neither agree or disagree/agree/strongly agree)
   a. I really liked working on the tasks
   b. I enjoyed working on the tasks
   c. Working on the tasks was fun
4. How satisfied were you while working on the task?
   (answers: strongly disagree/disagree/neither agree or disagree/agree/strongly agree)
   a. I felt satisfied working on the tasks
   b. I felt pleased working on the tasks
   c. I felt frustrated working on the tasks
5. After you performed these tasks, how easy or difficult were these tasks for you?
   (very difficult/somewhat difficult/neither easy or difficult/somewhat easy/very easy)
   a. Competitive analysis
   b. Product ad development
   c. Persona ideation
   d. Product name generation
6. After you performed these tasks, how routine or creative were these tasks for you?
   (very routine/somewhat routine/neither routine or creative/somewhat creative/very creative)
   a. Competitive analysis
   b. Product ad development
   c. Persona ideation
   d. Product name generation
7. Do you usually trust technology?
   (answers: strongly disagree/disagree/neither agree or disagree/agree/strongly agree)
   a. My typical approach is to trust new technologies until they prove me that I shouldn't
   b. I generally give a technology the benefit of the doubt when I first use it
   c. I usually trust a technology until it gives me a reason not to trust it
8. What do you think about AI collaborators?
   a. I personally feel that AI collaborators are (Very Artificial/Artificial/Neither artificial nor lifelike/LifelikeVery lifelike)

   b. I personally feel that AI collaborators are (Very machine-like/Machine-like/Neither machinelike nor humanlike/Humanlike/Very humanlike)
   c. I personally feel that AI collaborators are (Very fake/Fake/Natural/Very natural)
   d. I personally feel that AI collaborators are (Very unconscious/Unconscious/Neither unconscious nor conscious/Conscious/Very conscious)
9. Have you worked with an AI collaborator today?
   a. Yes
   b. No

IF YES:

10. Please answer these questions about your collaborator
(answers: strongly disagree/disagree/neither agree or disagree/agree/strongly agree)
    a. There was a good fit between what AI offered me and what I was looking for while working on the tasks
    b. My expectations are fulfilled very well by the collaboration provided by AI.
    c. The collaboration with AI gave me just about everything that I wanted from this collaboration
    d. The AI collaborator was reliable
    e. The AI collaborator was dependable.
    f. The AI collaborator was competent.
    g. The AI collaborator was able.
11. Based on your experience today, will you continue using the technology that you used today?
(answers: strongly disagree/disagree/neither agree or disagree/agree/strongly agree)
    a. I intend to continue using the technology I used for this task in the future
    b. I will always try to use the technology I used for this task
    c. I plan to continue to use the technology I used for this task frequently
12. How confident are you that the solutions you created today are of high quality?
    a. Not at all confident
    b. Slightly confident
    c. Moderately confident
    d. Very confident
    e. Extremely confident

Appendix B Participant's from the No collaborator group example answers

Participant's demographic information:

- *Female*
- *25-34 years of age*
- *Employed full time*
- Major in *IT*
- Usage of generative AI such as Lensa, Dalle-2, BERT or ChatGPT: *A lot*

Task answers

1. Enter the product name you came up with.

“Gum-Boom”

2. Describe the competitors analysis you performed

"a. Orbit, Hubabuba, Halls, Mentos, Donald, Turbo

b. regular chewing gums, sometimes whitening, sometimes with tastes, just to chew.

c. - First gum on a market giving energy boost, stress relief and fresh breath in such a small portion of gum

- easy accessible - shops, vending machines, petrol stations etc

- competitive price similar to competitors

- eye catching packaging

- marketing campaigns given by the influencers

d. Competitiors apply a borning sessions of chewing to make your breath fresh, to chew something between dishes. "

3. Describe the customer persona

"Persona for Gum-Boom is Julia, 22 years old and she is an active student of IT science. She is involved in Science Club at her university and is training ballroom dancing. During her active day she is taking a gum to have a boost in the morning, after intense classes where she has to make an intellectual effort, as well as after dancing classes.

She can buy Gum-Boom at the university and everywhere she is doing shopping. Between classes she is exhanging tases of Gum-Boom with her colleagues and is trying new sorts. Chewing is a new lifestyle for modern students. Gum-Boom packaging is a very good looking gadget and everyone wants it."

4. Create an add, basing on the persona and product description

"Gum-Boom art of living! and can show people in various situations when Gum-Boom can give you energy, fresh breath, keeps you calm."

Appendix C Participant’s from the Generative AI group example answers

Participant’s demographic information:

- *Male*
- *35-44 years of age*
- *Employed full time*
- Major in *Electrical Engineering*
- Usage of generative AI such as Lensa, Dalle-2, BERT or ChatGPT: *A little bit*

Task answers

1. Enter the product name you came up with.

"FreshFever"

2. Describe the competitors analysis you performed

“Wrigley's main competitors are Cadbury, Lotte, Perfetti Van Melle, and Hershey's. Strengths: Wrigley has a strong presence in the chewing gum market, with a wide variety of products and a strong brand name. However, its competitors also have strengths in their own areas. Cadbury has a strong brand name and reputation, while Lotte has a wide variety of products and a strong dealer community. Perfetti Van Melle is another major player in the confectionary market with popular brands like Alpenlibe and Big Babool. Finally, Hershey's offers unique and innovative products that have gained them a loyal customer base. Weaknesses: Wrigley's weaknesses include a limited product range and recalls of some products. Cadbury also has a limited product range, while Lotte has below average investment in Research and Development. Hershey's faces high competition from other manufacturers.

Examples of competitors' market approaches include: Pricing Strategy: Competitors may have different pricing strategies, such as charging a premium for high-quality products, offering discounts for bulk purchases, or offering promotional pricing. Product Positioning: Competitors may have different product positioning strategies, such as targeting a certain market segment, offering unique features, or emphasizing affordability. Product Mix: Competitors may have different product mixes, such as offering a variety of products in different categories or focusing on one particular product. Advertising: Competitors may have different advertising strategies, such as using traditional media, digital media, or a combination of the two. Distribution Network: Competitors may have different distribution networks, such as using a direct-to-consumer model or relying on third-party distributors. Customer Service: Competitors may have different customer service strategies, such as offering 24/7 support or providing a variety of customer support channels.”

3. Describe the customer persona

“The perfect customer for your new chewing gum would be someone who values freshness, fun, and excitement in a product. They should be health-conscious and looking for a product that is not only tasty but also provides additional health benefits. They should also be looking for product innovation, as well as convenience and portability when it comes to chewing gum. Finally, they should be seeking out a product that stands out from the competition and is unique in its offering.”

4. Create an add, basing on the persona and product description

“Are you looking for a way to get a boost of energy throughout the day, while also keeping your breath fresh and teeth white? Look no further than our new chewing gum! Our energy gum is designed to give you the energy you need to keep going, without the crash or jitters of energy drinks. Plus, it's formulated to help keep your breath fresh and your teeth white! Our gum is convenient and portable, so you can take it with you wherever you go. Try it today and experience the energy boost you need!"

[1] Our assistant has been trained to perform the following tasks: competitive analysis, persona ideation, ad from product description and product name generation.