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Augmentation or Replacement? Investigating the new frontier of Generative AI

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Abstract

The rapid advancement of Generative Artificial Intelligence (Generative AI) technologies, such as GPT-4, DALL-E, and Copilot, is revolutionizing many industries and consequently the workplace. This study examines the psychological and sociological implications of integrating Generative AI tools for routine and non-routine tasks, focusing on how these technologies influence workers' perceptions of being augmented by AI. Moreover, there is a focus on the moderating role of two agentic motives: self-enhancement and self-efficacy.

To fill this gap a 2x2 between-subjects experimental study was employed, with 200 participants completing a self-administered questionnaire through Qualtrics XM. In the survey, scenarios were created that showed both routine and non-routine tasks involving Generative AI, and then participants were asked questions to assess their perceptions, self-enhancement, and self-efficacy. Using SPSS, the data from 174 responses that were fully completed was analyzed and validated using exploratory factor analysis and reliability testing.

The results have confirmed the hypotheses, evidencing as for routine tasks delegating the job to generative artificial intelligence tools leads the workers to feel augmented. Additionally, self-enhancement and self-efficacy were found to moderate this relationship, highlighting the importance of individual psychological factors in the adoption and acceptance of AI technologies.

This study fills gaps in the literature regarding the interaction between Generative AI and human agency motives. The findings offer valuable insights for managers and organizations on effectively integrating AI into the workplace to enhance productivity and worker satisfaction while addressing ethical and psychological considerations. Future research directions and potential limitations are also discussed.

Keywords: Generative AI, Augmentation, human agency, job displacement, new technologies

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Introduction

In the recent years, Generative Artificial Intelligence (Generative AI) has endured an incredible growth and spread, radically transforming many industries. Tools such as GPT-4, DALL-E and Copilot are revolutionizing the way we work and communicate, pushing the boundaries of technological innovation. These artificial intelligence models, based on advanced neural networks and architectures like the Transformer, not only generate new and meaningful content, but are also creating new dynamics in the workplace.

The introduction of Generative AI raised fundamental questions about the interaction between humans and machines. The collaboration between artificial and human intelligence can generate a sense of increased capacity (augmentation) or, on the contrary, a feeling of substitution and threat (replacement). This duality raises crucial questions about the psychological and sociological implications of integrating artificial intelligence into work contexts.

This study aims to explore how the perception of being increased by Generative AI can be influenced by the nature of the activities carried out (routine vs. non-routine) and by two important human motivations: self-enhancement and self-efficacy. Self-enhancement refers to an individual's motivation to adapt their behavior to project a good self-image to others, while self-efficacy refers to confidence in their own ability to perform a specific task.

To address these issues, an experimental study was conducted using a questionnaire divided into four main parts, administered via the Qualtrics XM platform. The collected data were analyzed through the use of SPSS statistical software, employing exploratory factor analysis and reliability testing to validate the scales used in the conceptual model.

The aim of this research is twofold: on the one hand, to understand how the use of Generative AI tools for routine tasks can influence the perception of workers to be increased, and on the other, to investigate the moderator role of self- enhancement and self-efficacy in this relationship. Understanding these dynamics can provide important academic and managerial contributions, offering insights into how organizations can effectively integrate artificial intelligence in the workplace, improving worker satisfaction and productivity.

Ultimately, this study aims to fill existing gaps in literature regarding the interaction between Generative AI and human motivations, exploring to what extent these technologies can be perceived as tools of empowerment or threat in the modern work environment.

Chapter 1 – IMPLICATIONS OF GENERATIVE AI IN THE WORKPLACE AND INDIVIDUAL EXPERIENCE: A PSYCHOLOGICAL AND SOCIOLOGICAL PERSPECTIVE

1.1 Generative AI

1.1.1 Overview and relevance of Generative AI

For a long time now the development of artificial intelligence systems has increased and began to contaminate the everyday life. Artificial intelligence refers to machines created with the intention of simulating the human intelligence - perceiving, recognizing, learning and solving problems. In this field, the new frontier is created by the emergence of Generative Artificial Intelligence (AI). The term Generative AI refers to computational techniques that are able of generating seemingly new, meaningful content such as text, images, or audio from training data (Feuerriegel et al., 2023). And the diffusion of instruments such as GPT-4, Dall-E, and Copilot is revolutionizing the way we work and communicate.

This study focuses on an important class of Generative AI, large language models (LLMs). LLMs are neural networks models based on the Transformer architecture (Bubeck et al., n.d.). They, opposing to the previous world of computer software, do not require specific instructions but learn from examples, given by the wider data sets, and create outputs (Brynjolfsson et al., 2023).

There are four main factors that have driven the progresses made regarding the current generative AI systems: computing scale, earlier innovations in model architecture, the ability to "pre-train" using large amounts of unlabeled data and refinements in training techniques (Brynjolfsson et al., 2023).

Computing scale refers to the amount of data and resources that are devoted (Kaplan et al., 2020). In particular, firms are widely contributing to this scale, resulting in 175 billion parameters included in the GPT-3 model; meanwhile, the GPT-4 model is estimated to include 1.8 trillion parameters (Patel and Wong, 2023).

With regard to the model architecture, it is fundamental to highlight two key innovations: positional encoding and self-attention. Positional encodings keep track of the order in which words occur in a given output. On the other hand, self-attention assigns importance scores to each word in the context of the entire input. By using these instruments, large language models are able to capture long-rage semantic relationships in input text, even if it is divided into smaller segments and processed in parallel (Vaswani et al., 2017).

Another important characteristic is the fact the LLMs can be pre-trained on wide amount of unlabeled data. And given the larger amount of unlabeled data compared to labeled ones, LLMs can learn about natural language on a much larger training corpus (Brown et al., 2020). This means that these models are able to adapt to different kind of tasks and industries.

Lastly, the key factor regarding the possibility of refinements in training techniques refers to the capacity of "fine-tuning" LLMs to generate output that matches the priorities of a specific setting (Liu et al., 2023).

All these innovations have strongly improved these models' performance and in particular the Generative Pre-Trained Transformer (GPT) family that especially now has attracted a strong media attention.

Generative Pre-trained Transformer (GPT-3) (Floridi and Chiriatti, 2020), a large language model (LLM), has made an important advancement regarding the wide field of computerization. These LLMs have now established the automation era. In fact, Machine Learning models opposing to the previous world of computer software do not require specific instructions but learn from examples, given by the wider data sets, and create outputs (Brynjolfsson et al., 2023). So, it is important to highlight a characteristic that distinguish Machine learning systems from computer programs: they are able to perform tasks even if no instructions exist, including tasks that require tacit knowledge that only lived experience could teach (Brynjolfsson and Mitchell, 2017).

Chat GPT is an example of application of machine learning. In particular, its function is given by the transformer architecture (Vaswani et al., 2017), as previously explained, that allows this model to understand the importance of words within sentences. The transformative model has been the key element in creating a nuanced language processing that previously was unfeasible. LLMs learn patterns and relationships between words and phrases and are then able to make predictions about what comes next only based by the context (Frey & Osborne, 2023). Though large language model implies human language, it is possible to apply the same techniques to produce other forms of sequential data such as computer code, chess moves, or protein sequences (Eloundou et al., 2023).

The relevance of Generative AI is multifaceted, covering not only mind-blowing technological achievements but also important sociological impacts. Also, industry reports suggest that generative AI could raise global gross domestic product (GDP) by 7% and replace 300 million jobs of knowledge workers (Goldman Sachs, 2023).

1.1.2 Generative AI and human collaboration

The story behind the collaboration of humans and Artificial Intelligence has begun far long ago.

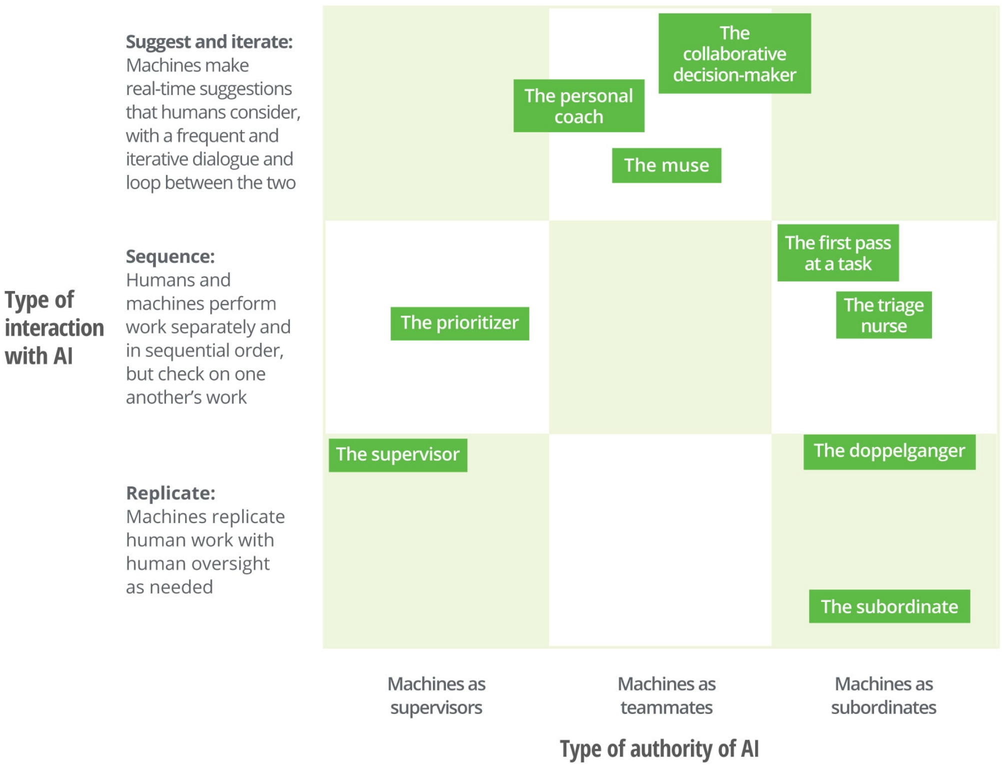
In fact, it was Licklider (1960) that already conceptualized the notion of combining human and machine intelligence through the term “man-computer symbiosis”. His view was about a cooperative interaction between men and electronic computers in order to enable men and computers to cooperate in making decisions and controlling complex situations without inflexible dependence on predetermined programs. This early vision has evolved into what is now often referred to as centaur systems, where AI does not replace human intelligence but complements it. In modern settings, this involves symbiotic relationships where both human intuition and AI capabilities are leveraged to optimize outcomes (Agni Orfanoudaki et al., 2022).
The concept of centaurs as the combination of the power of artificial and human intelligence finds its origins from the Greek mythology, according to which they were half-human and half-horses creatures. This image has been translated into modern times for systems that allow a form of superior decision-making that combines the power of man with that of trained algorithms (Soroush Saghafian, 2023). One of the main users in the U.S. has been the Defense Department, which has been working with tech companies to combine the power of algorithms with the capabilities of humans. Both the Defense Advanced Research Projects Agency and the Pentagon's third-offset strategy for military advantage have shown interest in the concept from the U.S. military (“Pentagon Turns to Silicon Valley for Edge in Artificial Intelligence (Published 2016),” 2024). For example, Robert O. Work, who was Deputy Secretary of Defense for Presidents Trump and Barack Obama, championed the concept of centaur weapons systems, which would necessitate human control instead of A.I.-based robot killers currently known as lethal autonomous weapons (“A Case for Cooperation between Machines and Humans (Published 2020),” 2024).
Originally the term centaur was used in the chess world, where the combination of humans and computers programs systematically defeated unassisted software. In fact, the chess legend Gary Kasparov has stated that the partnership between human and algorithms can do better than just the single strongest computer program (Garry Kasparov on AI, Chess, and the Future of Creativity (Ep. 22), 2018).
Another application of the centaur model can be found in clinical decision-making, more specifically regarding the rehabilitation assessment. Here, algorithms provide therapists with detailed analysis on patient’s status and improve the practices of rehabilitation assessment. In fact, it was proven that an artificial intelligence (AI)-based system can provide therapists with quantitative insights on the status of a patient, improving their experiences and agreement level of rehabilitation assessment. This system can predict assessment and generate patient-specific analysis by identifying salient kinematic features of decision making in rehabilitation assessment instead of presenting abundant quantitative data for expert review (Lee et al., 2021).

"Large language models, like image generation AI systems, are increasingly powering human-machine collaborations involving prompts from humans interacting with AI in the workplace" ("Human-machine collaboration | Deloitte Insights"). Articles, conversations, blog posts, product descriptions, and multiple other content types can be created by systems like OpenAI's GPT-3 and Google's LaMDA in response to human prompts. They have the ability to create programming code and serve as a coding mentor for multiple languages. One engineer emphasized how different collaborating with AI is from collaborating with human colleagues: "It's a very foreign intelligence, right? It's not something you're used to. It's not like a human theory of mind. It's like an alien artifact that came out of this massive optimization (Thompson, 2022).

There are different ways workers can interact with AI, ranging from people working with AI to supervise AI's work (machines as subordinates), to people working with AI in a way that directs their work (machines as supervisors), to people working with AI in open-ended, highly iterative, and interactive ways over time in true partnership (machine as teammates) ("Human-machine collaboration | Deloitte Insights").

FIGURE 1

The many ways humans can friend a machine at work



Type of collaboration	Definition
The supervisor	An algorithm allocates tasks—for example, a ridesharing company that uses AI to dispatch rides to drivers who have a few seconds to accept or reject a ride request without knowing the destination or fare. Performance and pay are determined by AI. An algorithm also decides when morale-boosting motivational messages are needed.
The prioritizer	An AI algorithm addresses a list of tasks—sales leads to be pursued, medical problems to solve, fundraising opportunities to follow up on—and ranks them in terms of their importance or potential value. The human worker then pursues them in order, sometimes with suggestions from the machine about how to do so.
The personal coach	AI discovers the human worker's strengths and opportunities for improvement on a specific task (such as a telephone or video sales call), resulting in continuous engagement with AI to improve the human's performance.
The muse	Multiple creative suggestions are prompted by a human, output by a machine, and iterated in an ongoing collaboration. Examples include design suggestions based on architect prompts and AI-driven generative design.
The collaborative decision-maker	Complex decisions, such as medical diagnoses, are made in a dialogue between AI and humans, and where AI can improve decisions by enumerating available options, helping people weigh them objectively, and suggesting the highest probability of successful action.
First pass at a task	A machine performs the first pass at a task—a life insurance application, a medical-coding categorization, an analysis of an MRI scan—and makes a preliminary decision or judgement. The human worker reviews the analysis and determines if it is correct. The order of this sequence could also be reversed.
The triage nurse	AI assesses the problem (medical symptoms, for example) and decides whether a human consultation is necessary; if not, it dispenses advice to address the relatively minor problem.
The doppelganger	Machines learn from a human or group of humans to mimic their behaviors and decisions, so that the human(s) can be replicated digitally.
The subordinate	AI systems perform menial, structured tasks (like extracting key data from documents or faxes) under human supervision and review.

It is by now common to see types of interactions with machines as subordinates or supervisors, as happens for warehouse workers and rideshares drivers whose jobs involve largely taking tasks and directions from AI systems (Cantrell et al., 2022).
On the other hand, it is still uncommon to see an interaction with machines as teammates. An example happened in the summer of 2022 when Jason Allen, a board game designer, won an art competition with a painting developed by using a generative AI tool that turns plain language queries into unique images. His painting, titled *Théâtre D'opéra Spatial*, was at the center of heated controversy, because while the painting was beautiful in the eyes of the judges, artists and critics immediately expressed outrage that the painting represented "the death of artistry" and that his effort represented "the literal definition of "pressed a few buttons to make a digital art piece" (Metz, 2022). What these critics didn't know was that the process wasn't so simple. In fact, it is estimated that Allen spent approximately 80 hours testing and improving different textual prompts in the AI tool, tweaking the image output digitally, and enlisting multiple digital tools to create a collaborative painting effort between a human and a machine (Pueblo Chieftain, 2022).
Such collaborations between humans and machines are creating a huge question regarding the identity, the allocation of rewards when work is done by both humans and AI, and even the future of the workforce experience when work is done not just by people but is the result of a collaboration between people and AI.
Over the past decade, there has been an explosion of AI tools that aim to empower workers by automating routine work, allowing human workers to focus on more complex and nuanced tasks. This is only a narrow form of human and machine collaboration. Workers can benefit from a more valuable form of collaboration between humans and machines by consistently interacting with AI, which requires workers to not only 'friend' and collaborate with their human colleagues, but also to 'friend' and collaborate with smart machines (Cantrell et al., 2022).

1.1.3 Generative AI on jobs

As the marvelous functions of Artificial Intelligence spread through the society, a new tension is arising regarding the possibility that this new instrument may generate a sense of augmentation or replacement while relying on AI systems. This dual possibility of experiencing a sense of enhancement and replacement highlights the urgence of better understanding the broad implications of AI's integration into various sectors. As was previously forecasted by Davenport et al.'s research (2018), the application of AI is valuable for information-intensive domains such as health care, marketing, financial services, professional services, education.
The impacts of Generative AI on various industries are a reality that we are now facing every day.

It is possible to see AI-driven tools assisting doctors during their work life, even if AI algorithms have shown to be biased and have led to failures in assigning "high-risks" scores that would have resulted in additional resources and attention from care providers, taking away from patients the additional help they would otherwise have received (Obermeyer et al., 2019).
GenAI will also have impact on how the marketing industry operates. Ma and Sun (2020) highlight that the application of artificial intelligence (AI) in marketing strategies has high potential for transformation. This is being manifested in the cases where prompt engineering becomes a useful skill for agencies and brands that will help them come up with ideas more quickly and then sell and promote an idea in a more fully formed way internally to teammates. Reisenbichler et al. (2022) observed that the underlying generative AI (GenAI) augured very well for boosting performance in marketing content with very significant cost savings, as said earlier by Noy and Zhang (2023), who noted the enhanced efficiency in tasks and improvement in the quality of output. CoPilot users reported increased satisfaction and efficiency with regard to the coding tasks provided by GitHub.
As the world of organizations seeks to obtain the best business results, it is difficult to conceive that there will be a facet in marketing untouched by GenAI. Its technology at the same time is expected to democratize marketing for the majority of enterprises, such as startups, small businesses, and organizational or professional creatives that would gain from Generative AI. The idea of being able to create customized messages or sales pieces for targeted parts of the audience exceeds all expectations. However, the effectiveness of these novel marketing approaches requires thorough validation across various contexts.
Even more, Generative AI's impacts may democratize business and cultural activities. Tools like DALL·E 2 are indicative of how Generative AI is going to lower the entry barriers for creative activities, allowing many more people than just formally trained artists and creators to produce new works in everything from the most traditional to the most cutting-edge media (Hippel, 2020). Democratization could bode very well towards speeding up user-driven innovations and, in fact, even revolutionize sections such as 3D printing and mass customization. A change that sounds the opportunity to prompt more convincing questions regarding the Generative AI influence on the design process and the resulting implications for consumer value and market dynamics (Hippel, 2020).
Furthermore, Generative AI may improve firms' crowdsourcing so that consumers can be better involved in the firm's innovation processes, particularly regarding tasks traditionally considered hard to be managed, such as product design (Schreier, 2017). This would mean revisiting the role of expertise and firms in product development and the wider market and welfare consequences. The rise of Generative AI therefore brings up important considerations for the creativity and

innovation management domain, even challenging the status quo theories and practices (Bouschery et al., 2023). For example, IBM has partnered with the Institute of Culinary Education in light of the "Cognitive Cooking with Chef Watson" project to show how Generative AI can come out from the area of human creativity limitations and easily find another couple of new compositions of culinary products. This example brings to light rethinking regarding the possibility by which human beings could utilize Generative AI in combing a large solution space, the benefits of performance that it provides, and what kind of skills would be required to work in a Generative AI world.

ChatGPT has been disruptive also in the field of education, serving as an assistant in learning and teaching activities. For students, ChatGPT can help in a variety of activities such as searching for information, answering to specific questions, and enhancing writing in a variety of languages. On the other hand, ChatGPT can be useful for teachers too. For example, it can be used for generating teaching plans, preparing teaching materials, reviewing and grading assignments, and even providing feedback to students. ChatGPT thanks to its nature as a LLMs is able to create educational content, personalize learning experiences, and improve student engagement (Kasneci et al., 2023), which means an improvement of the overall efficiency and effectiveness of education delivery. Regarding the academic research, the support that ChatGPT can offer covers all kind of activities, from the problem formulation to the research design and the data collection and analysis, as well as reviewing and critiquing the writing and composition (Susarla et al., 2023).

It is a common argument the problem that using generative AI may create job displacement. Although AI does not only have the power of automating worker tasks but also augmenting those tasks (Brynjolfsson et al., 2023). There are people that tend to consider Generative AI as the advocator of a jobless future (Ford, 2015; West, 2018), while on the opposite side there is a more positive vision according to which Generative AI will enrich human productivity and work experiences (McKinsey Global Institute, 2017).

Previous research has analyzed that utilizing ChatGPT increases average productivity resulting in decreasing the time taken and rising the output quality (Noy and Zhang, 2023). According to Noy and Zhang's study ChatGPT also increases job satisfaction and self-efficacy. At this point, it is easy to worry about the future that certain job positions may have. New generative AI tools such as ChatGPT and DALL-E are the new frontier of creativity, as through the introduction of machine learning systems they have the ability to learn and create perfect products. Despite these worries it was proved that the overall optimism increased after discovering ChatGPT's potential (Noy and Zhang, 2023). In addition, the AI's capacity of replicating and in some cases exceeding human-level intelligence in a variety of tasks is anticipated that would change the types of workers skills demanded. Resulting not in a replacement of human work but just in a changing of what skills firms will require (Davenport et al., 2018).

Endorsing the believing that Generative AI will not replace jobs it is the fact the LLMs are prone to hallucinations, meaning that they sometimes fabricate content and even references. In fact, while the previous versions of natural language systems were concerned with the problem of degeneration, meaning bland or incoherent output text, or that which gets stuck in repetitive loops (Holtzman et al., 2020), the recent problem concerning the current systems is that LLMs tend to generate plausible sounding, yet erroneous information. Hallucination is not only a problem in relation to large language models' functional ability but also relating to their safety. To overcome and diminish these hallucinations, it is important to properly train the system and test it using a varied and representative data set. Furthermore, could be useful incorporating methods of monitoring and detecting hallucinations, among others human evaluation (Lemos & Martins, n.d.).

This propensity to hallucinating surely assures that in the near future firms will not want to leave consumers' relationships in the exclusive hands of an AI that could hallucinate so easily (Frey et al., 2023). An example is given by Amazon, that has left the leading of important brands like Nestlé SA and Propter & Gamble Co in the hands of a human account manager, while uses AI for smaller contracts that otherwise would not be considered.

1.1.4 Generative AI's limits

Generative AI has not yet been perfected and this is the reason why it shows some limitations.

Firstly, as previous mentioned a widely recognized limitation of generative AI is the phenomenon of hallucination, that happens whenever contents generated are nonsensical or unfaithful to the given source input (Ji et al., 2023). According to Azamfirei et al. (2023) there is a better term to describe the hallucination phenomenon and it is "fabricating information" or fabrication.

Another challenge of this technology concerns the quality of training data that largely influence the quality of generative AI models (Dwivedi et al., 2023). Any factual errors, unbalanced information sources, or biases embedded in the training data may be reflected in the output of the model (Nah et al., 2023). To handle this issue regarding the quality of datasets, is necessary to execute data cleansing for the training datasets even if is overwhelmingly expensive given the massive amount of data. Synthetic training data could be used to not only ensure the diversity of the datasets but also to address sample-selection biases in the datasets (Chen et al., 2021).

Further, there is a current concern regarding the lack of explainability for the model, which means information about how the algorithm arrives at its results is deficient (Deeks, 2019). In particular, for generative AI models it refers to fact that there is no transparency of how the model arrives at the results (Dwivedi et al., 2023). As consequence there might raise several issues. Difficulty for users to comprehend and understand the output (Dwivedi et al., 2023). Difficulty for users to discover potential mistakes in the output (Rudin, 2019). In addition, users may have problems trusting the system and their responses or recommendations (Burrell, 2016). Lastly, as for the perspective of law and regulations, it would be hard for the regulatory body to judge whether the generative AI system is potentially unfair or biased (Rieder and Simon, 2017).

Additionally, the ability to interact with AI efficiently and effectively has become one of the most important media literacies. So, it is fundamental that generative AI users learn and apply the principles of prompt engineering, which refers to a systematic process of carefully designing prompts or inputs to generative AI models to elicit valuable outputs. Given the ambiguity of human languages, it is very important that the quality of prompts is high. Another challenge is to debug the prompts and improve the ability to communicate with generative AI (V. Liu and Chilton, 2022). Therefore, it is imperative to provide training about prompt engineering, especially for those who are most frequently engaged in interaction with generative AI.

1.1.5 Ethical concerns

In the context of AI, ethical concerns refer to the moral obligations and duties of AI application and its creators (Siau and Wang, 2020).

First and foremost, there is the challenge concerning harmful or inappropriate content. In fact, content produced by generative AI could be violent, offensive, or erotic (Zhuo et al., 2023). Even if OpenAI has set up a content policy for ChatGPT, harmful or inappropriate content can still appear due to reasons such as algorithmic limitations or jailbreaking (i.e., removal of restrictions imposed). The language models' capacity to understand or generate harmful content is referred to as toxicity (Zhuo et al., 2023). Due to the harm to society and damage that toxicity can bring to the community, it is crucial to ensure that harmful or offensive information is not present in the training data, and it is removed whenever it is present (Nah et al., 2023).

Then, an issue is represented by the concept of bias, that refers to the inclination that AI-generated responses or recommendations could be unfairly favoring or against one person or group (Ntousi et al., 2020). Biases occur by different forms: training data representing only a fraction of the population may create exclusionary norms (Zhuo et al., 2023); training data in one single language (or few languages) may create monolingual (or non-monolingual) bias (Weidinger et al., 2021), so cultural sensitivities to different regions are crucial to avoid biases (Dwivedi et al., 2023); bias may emerge in employment decision-making if generative AI is used (Chan, 2022). Hence, to ensure fairness and avoid biases, it is crucial to ensure that the training data is representative, complete, and diverse (Gonzalez, 2023). And also, here the use of synthetic data for training can increase the diversity of the dataset and address issues with sample-selection biases in the dataset (Chen et al., 2021).

Another ethical issue that is important to address is the over-reliance that can arise from the convenience of generative AI. Because users end adopting answers by generative AI without careful verification or fact-checking (Iskender, 2023; Van Dis et al., 2023). This is a problem because over-reliance can impede skills such as creativity, critical thinking, and problem solving (Iskender, 2023) and create human automation (Van Dis et al., 2023).

A critical challenge, especially regarding education, is the misuse of generative AI, which means any deliberate use that could result in harmful, unethical or inappropriate outcomes (Brundage et al., 2020). This issue may appear as plagiarism for assignments and essays using texts generated by AI (Cotton et al., 2023) or as cheating in examinations or assignments using generative AI (Susnjak, 2022). To address this problem there are many suggestions made. On one hand, the employment of AI-generated content detectors such as Turnitin (Susnjak, 2022). On the other hand, researchers have offered suggestions and recommendations on how generative AI could be used in the responsible conduct of scholarly activities (Susarla et al., 2023).

An additional issue is data privacy and security. Privacy regards the sensitive personal information that owners do not want to disclose to others (Fang et al., 2017), and data security the practice of protecting information from unauthorized access, corruption, or theft. Here the fear relates to fact that generative AI may disclose sensitive or private information (Siau and Wang, 2020). The resolution might be for users to be careful when disclosing personal and sensitive information during the usage of generative AI tools (Nah et al., 2023).

Finally, the last ethical challenge that is necessary to analyze is the so called digital divide. The digital divide is often defined as the gap between those who have and do not have access to computers and the Internet (Van Dijk, 2006). Then, a second-level digital divide emerged, which refers to the gap in Internet skills and usage between different groups and cultures (Scheerder et al., 2017). Now, the emerging generative AI may widen the existing digital divide in society (Carter et al., 2020). To avoid the digital divide or at least to reduce its effects, having more accessible AI and AI literacy training would be beneficial (Nah et al., 2023).

1.1.6 Generative AI augmentation

At the heart of this research, it is the concept of Augmentation. This feeling can emerge by the fact that by delegating some tasks to the generative AI the worker is able to focus entirely on activities that he finds more satisfactory and meaningful: working less and just enjoying the positive effects of leisure (Fishback and Choi, 2012), or working better by delegating extrinsically motivated tasks to AI and keeping intrinsically motivated tasks for themselves (Botti and McGill, 2011). Another possibility could be the fact that workers can focus on activities that they master and leave to AI those on which they lack capabilities (Puntoni et al., 2020). This is a way they can enhance self-efficacy, the personal belief a person maintains as to how well they can perform a task (Huffman et al., 2013).

This concept has captivated interests from many and an example is IBM's Institute for Business Value (2023) that proposes five best practices for achieving the principle of augmenting human intelligence.

First, using AI to augment human intelligence, rather than operating independently of, or replacing it (AI Revolution: Impact Series | Barclays Investment Bank, 2023).

Secondly, in a human-AI interaction, they point out the importance of notifying individuals that they are interacting with an AI system, and not a human being (AI Revolution: Impact Series | Barclays Investment Bank, 2023).

Moreover, it is important to design human-AI interactions to include and balance human oversight across the AI lifecycle. Address biases and promote human accountability and agency over outcomes of an AI systems (AI Revolution: Impact Series | Barclays Investment Bank, 2023).

Another practice regards the development of policies and practices to foster inclusive and equitable access to AI technology, enabling a broad range of individuals to participate in the AI-driven economy (AI Revolution: Impact Series | Barclays Investment Bank, 2023).

Finally, it is proposed to provide comprehensive employee training and reskilling programs to foster a diverse workforce that can adapt to the use of AI and share in the advantages of AI-driven innovations. So, collaborate with HR to augment each employee's scope of work (AI Revolution: Impact Series | Barclays Investment Bank, 2023).

1.1.7 Generative AI replacement

On the opposite side, the use of Generative AI may generate a sense of replacement. In fact, just knowing that AI is capable of acting as a substitute for human labor can be psychologically threating. Firstly, because people have a powerful desire to attribute outcomes to one's own skills and effort (Bandura, 1997; Leung et al., 2018). Studies have proven that computers are often seen as disempowering by humans because they prevent them from having a sense of accomplishment when doing something. This is why humans tend to credit themselves for positive outcomes and blame computers for negative ones (Moon and Nass, 1998). In addition, there is the fear that utilizing generative AI could be seen as cheating (Puntoni et al., 2020).

Secondly, because outsourcing work to machines prevent people from practicing and improving their skills, which negatively impacts self-worth and contribute to a satisficing tendency by which individuals settle for a level of engagement that is just good enough (Puntoni et al., 2020). An example is stated by the journalist John Seabrook (2019) which found himself in a surreal situation while writing an email to his son. In fact, after having typed just a few letters Google's Smart Compose already suggested the end of the sentence. The journalist was overwhelmed by this action because he found himself deprived by an ability that he had always considered unique to our species.

Lastly, outsourcing tasks to GenAI can lead workers to experience a loss of self-efficacy. Self-efficacy is heightened when individuals are actively engaged in creative tasks (Dahl and Moreau, 2007; Norton et al., 2012). An example that easily explain this feeling is the use of GPS. In fact, there is the case of tourists that drove a car into the ocean because they were following the GPS' directions and didn't change the road because they completely relied on it (Milner, 2016).

1.2 Human Agency

There is a fundamental force that drives human behavior that is called agency, a self-focused orientation aimed at developing and enhancing the individual self (Abele et al., 2007). It is usually linked to people's consumption habits. In fact, it is common to see people who spend a substantial amount of money to buy a luxury item that proves their status. Or they could spend money to buy something that could improve their skills such as a training course.

According to Cannon and Rucker's study, agency may arise from two distinct motives: self-efficacy and self-enhancement. Self-efficacy, as previously mentioned, regards one's desire to improve his own skills and abilities (Bandura, 1982). Meanwhile, self-enhancement reflects the desire to view oneself positively and achieve a sense of social superiority (Paulhus, 1998).

Both self-efficacy and self-enhancement are connected to agency because they both lead to a self-focused direction and generate similar self-focused outcomes (Cannon and Rucker, 2022). But, while self-efficacy motives may lead someone to improve the self regardless of whether the improvement is seen by others, self-enhancement motives tend to drive people to appear better no matter the action may generate any kind of improvement.

According to psychologist Alfred Bandura (1982), self-efficacy influences learning and performance in several ways. It affects the goals that employees choose, the effort they put into learning new tasks, their persistence in the face of challenges, their resilience after setbacks, and the amount of stress they experience when engaging in tasks. High self-efficacy leads to a positive approach toward difficult tasks, deeper engagement with work-related challenges, and a quicker recovery from setbacks. Low self-efficacy leads to negative outcomes like avoiding difficult tasks and quickly losing confidence in one's abilities. Self-efficacy beliefs are central to employee performance and motivation, making it crucial for managers to enhance these beliefs to improve productivity.

Self-enhancement motives influence job performance behaviors by motivating employees to enhance their self-image through performance and organizational citizenship behaviors (OCBs). These behaviors reflect an employee's efforts to impress management, especially when their role is not clearly defined, which is known as high role ambiguity. Employees tend to engage in OCBs and work harder to improve task performance when motivated to enhance their self-image, particularly in ambiguous roles.

In the workplace, these motives affect behaviors such as task performance and OCBs. Employees with high self-enhancement motives are more likely to exhibit behaviors aimed at impressing management and seek to improve their image, which can involve exceeding formal job requirements. Their efforts to improve performance and engage in OCBs may result in managers viewing them more favorably and recommending higher rewards (Yun et al., 2007).

1.3 Gap in literature

Previous research has highlighted that when given access to ChatGPT professionals increases their productivity for writing tasks experience. In fact, the Generative AI tool not only increases the quality of the output for low-ability workers, but it also allows high-ability workers to maintain their outputs' standards in way less time. These results were proven to increase the job satisfaction and self-efficacy of these workers (Noy and Zhang, 2023). However, this study only focused on singular and fast tasks, and this can't give enough evidence of what the sentiment regarding the whole job is.

There is a wide vastness of research concerning the psychological consequences of agency or the analysis of self-efficacy and self-enhancement motives in isolation (Cannon and Rucker, 2022). Though, there are some gaps in the literature that could be interesting analyze.

First of all, there is no study that focused on the link between the perceived augmentation due to the utilization of Generative AI and the agentic motives of the worker. In fact, it is suggested to explore whether a variable exerts its effects because of self-efficacy or self-enhancement specifically, or a combination of both through interactive effects (Cannon and Rucker, 2022). Moreover, it could be interesting to analyze if there are some situations when people are more prone to adopt a self-efficacy or self-enhancement motive. Because it could be possible that viewing a situation as a challenge may trigger the response to demonstrate self-mastery and achievement (Blascovich et al., 2000).

1.4 General purpose of the study and research question

Generative AI models such as ChatGPT, Midjourney, and DALL-E are among the most disruptive technology breakthroughs in recent years (Dwivedi et al., 2023). With the ability to produce new content such as text, videos, and images generative AI models are regarded as the next milestone of artificial intelligence (Luo et al., 2023). Generative AI bears potential for a wide range of applications in various sectors such as business, education, healthcare, and content creation industries. Yet, there are some challenges that comes with this new technology. An important one is the fear that Generative AI may create job displacements and let workers feel replaced.
The previous literature review aimed to analyze the factors that enhance the necessity of a human-centered approach according to which Generative AI should not work alone but will require a constant human collaboration.
In addition, it is fundamental to understand which psychological factors may affect people's relationship with Generative AI. This study aims to investigate whether self-efficacy and self-enhancement motives influence the workers' perceptions while using Generative AI tools. To address this issue, the research question is formulated as follows:

"To what extent do self-efficacy and self-enhancement motives influence workers' perceptions of being augmented by Generative AI in their roles?"

Chapter 2 – Conceptual framework and Hypotheses development

2.1 Routine & Non-routine tasks on workers' perception of being augmented by GenAI

It was already argued in the past that computerization affects different categories of tasks that employees perform in the workplace in various ways (Autor et al., 2003).
The emergence of powerful generative AI tools has brought it up again the discussion regarding automation (Noy and Zhang, 2023). And the fear of being replaced by AI technologies is now

stronger than ever. In fact, previous studies have claimed that automation technologies mostly displace human workers and increase unemployment (Acemoglu and Restrepo, 2018). On the other hand, it is also believed that automation complements existing workers and raise their productivity (Agrawal et al., 2019).

During this study, qualitative research was conducted to analyze better how people consider the many tasks they have to complete while working. The qualitative research was submitted in the form of a survey in which there were 4 questions that participants (N=44) had to answer describing at least one working situation in which they had used a generative artificial intelligence tool and felt that they had been augmented by it. Most of the cases described were work tasks that they considered boring or routine. The term "routine tasks" is used for limited and well-defined set of cognitive and manual activities that can be accomplished by following explicit rules (Autor et al., 2003). And due to their nature, it was proven that routine tasks are more susceptible to automation and computerization than non-routine tasks (Mertens and Romeu-Gordo, 2023). However, ChatGPT was proven to increase job satisfaction by automating tedious or annoying components of the task or allowing people to finish more quickly (Noy and Zhang, 2023).

Here, the scope of the research is to analyze whether using Generative AI tools to complete routine tasks is more likely to make workers feel augmented rather than using it for non-routine tasks.

H1: Routine tasks (vs. non-routine tasks) will positively (vs. negatively) impact the workers' perception of being augmented by Generative AI tools

2.2 The moderating role of human agency

Previous research has highlighted that impression management is a common phenomenon in the workplace (Wayne and Liden, 1995). And to impress others, workers may engage in different behaviors.

It is common knowledge that high performers employees are needed and valued by organizations. So, employees who achieve higher levels of performance are likely to be more valued and to be viewed more favorably by others, and their performance will be recognized and rewarded. Thus, employees can impress others, including their immediate managers, by achieving a higher performance than expected. Recognizing this, employees who are highly motivated to enhance their self-image may try harder to improve their task performance. On the other hand, employees who lack motivation and do not want to impress their managers may limit their work effort, leading to a limited output (Yun et al., 2007).

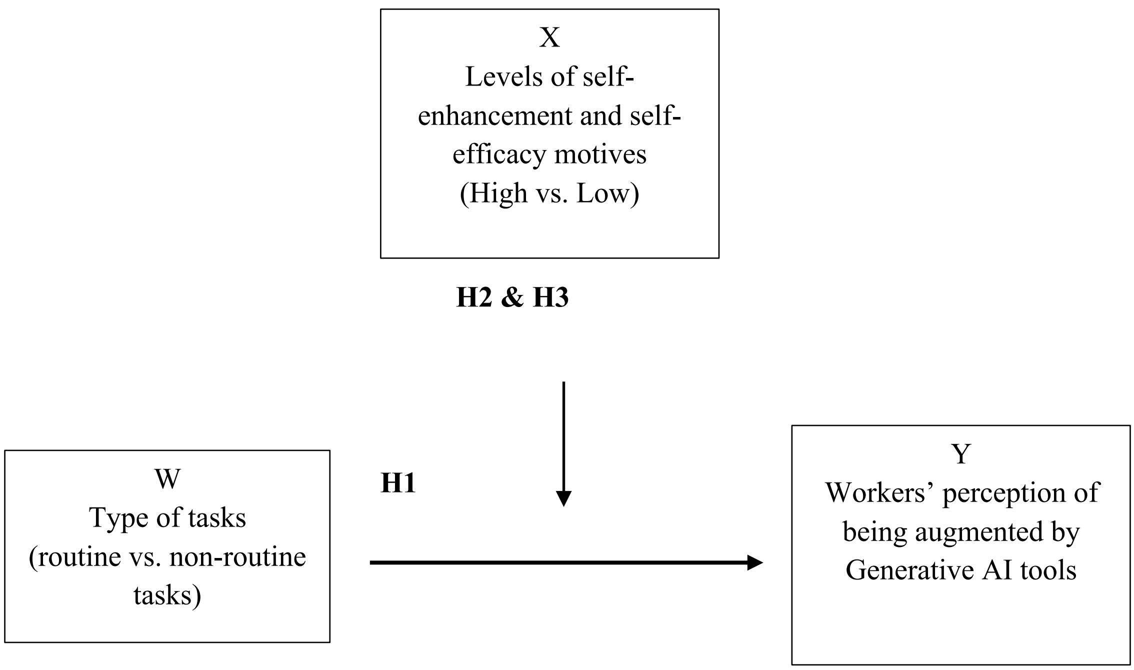
Noy and Zhang's (2023) study confirmed that the use of Generative AI improves the workers' productivity but did not remove the fear of replacement due to the use of Generative AI tools.

This study aims to research conditions according to which workers may feel augmented while using Generative AI tools. In particular, the hypothesis here reflects on the possibility that people with high level of self-enhancement will more likely see generative AI tools as instruments that will augment their capabilities and let them improve their performances.

H2: High level of self-enhancement motive will positively moderate the relationship between routine tasks and the workers' perception of being augmented by Generative AI tools. Specifically, where there are high levels (vs. low levels) of self-enhancement motive, routine tasks (vs. non-routine tasks) will make the workers feel more augmented.

Moreover, according to Bandura (1986), when a person aspires to a high achievement goal, she is more apt to exert the self-monitoring and to sustain the efforts required to reach a satisfactory solution. In addition, when requisite knowledge and skill are lacking a sense of self-efficacy for learning is beneficial because it motivates individuals to improve their competence (Schunk, 1995).
Consequently, it is expected that workers with high level of self-efficacy motive (vs low level of self-efficacy motive) will perceive themselves augmented (vs replaced) while using Generative AI tools.

H3: High level of self-efficacy motive will positively moderate the relationship between routine tasks and the workers' perception of being augmented by Generative AI tools. Specifically, where there are high levels (vs. low levels) of self-efficacy motive, routine tasks (vs. non-routine tasks) will make the workers feel more augmented.



Chapter 3 - Experimental research

3.1 Methodological approach

3.1.1 Methodology and study

This experimental study consists of a conclusive causal research design between subjects 2x2. The results of the experiment are represented by the responses to a questionnaire obtained through a self-administered survey conducted in Italy during May 2024 using the online platform Qualtrics XM. The survey participants were selected using a non-probabilistic sampling methodology, specifically a convenience sampling method, leveraging the ease and speed of access and selection of the sample population elements. Indeed, this technique incurs no economic cost and is advantageous in terms of both a high data collection speed and a high response rate. Considering the target sample, it was decided to include respondents of all ages, collecting data from both male and female individuals, as demographic variables were not expected to statistically significantly influence the experiment's results.

3.1.2 Participants and sampling procedure

The survey was distributed to 200 individuals, of whom 174 respondents fully participated in the experimental study, providing complete and thorough answers to all the questions within the questionnaire structure. The remaining 26 incomplete responses were first selected and then discarded from the dataset during the data cleaning procedure. Respondents were contacted through an anonymous link generated by the Qualtrics XM online platform, which was subsequently sent via instant messaging applications and social media networks as the primary distribution channels (WhatsApp and Instagram).

The target population sample reached by the survey mainly included graduating university students and recent hires located in various cities across Italy. Therefore, based on this assumption, the average age of respondents was found to be 27.59 years, although the age range varied from a minimum of 20 to a maximum of 74 years. Regarding the gender of the respondents, the predominant gender in the sample was female, represented by 49.4% (86/174), while the male gender was characterized by 45.4% (79/174). The remaining 5.2% (9/174) of respondents preferred not to identify with a specific gender (2.9%; 5/174) or selected the third gender/non-binary option (2.3%; 4/174).

3.1.3 Data collection and questionnaire composition

To conduct the experimental study, it was necessary to develop a questionnaire consisting of 14 questions, 12 of which were specific and 2 demographic. To manipulate the independent variable (Type of Task: Routine vs. Non-routine), it was essential to create two distinct visual stimuli.
The first scenario consisted of an immersive text featuring a routine task that involved the use of Generative AI. The second scenario consisted of an immersive text featuring a non-routine task that also involved the use of Generative AI.

S1

You are an employee at a company, and one of your daily tasks is to write and send emails to customers to provide updates on their orders. Usually, these emails follow a standard format and only require you to insert specific information for each customer. The company has recently implemented the use of ChatGPT, a generative artificial intelligence tool, to assist with writing these emails. Now, you are asked to use ChatGPT to completely write these emails, simply inputting basic information (such as the customer's name and order details). ChatGPT takes care of creating the entire email content, which you then just need to send.

S2

You are an employee at a company, and one of your occasional tasks is to develop creative projects for presentations to your superiors. These projects require a significant amount of brainstorming, innovation, and creation of original content to impress your audience. The company has recently implemented the use of ChatGPT, a generative artificial intelligence tool, to assist with content creation. Now, you are asked to use ChatGPT to completely develop the creative project. You only need to input the general topic and a few key points, and ChatGPT takes care of generating the entire project, including creative ideas, textual content, and even suggestions for the presentation.

As previously mentioned, the data was collected using a questionnaire, which is divided into four main parts.
At the beginning of the questionnaire, there was a brief introduction along with an explanation of the academic purpose of the experimental research. Additionally, after including the university's credentials, full compliance with privacy regulations regarding the anonymity policy in data collection and management was ensured.
The second part of the survey consists of a randomized block composed of two distinct scenarios. The randomization process was essential within the questionnaire structure to obtain an even number of exposures to both textual stimuli. To avoid potential cognitive biases and any brand sentiment conditioning, both scenarios are represented by two immersive test mock-ups without

any reference to real brands. Therefore, both textual conditions were created independently.
The third part of the survey was introduced to respondents after they were exposed to one of the two scenarios. This block of the questionnaire consists of 12 questions: the first three related to the first moderator (self-enhancement), another three regarding the second moderator (self-efficacy), another three concerning the dependent variable (perception of being augmented by GenAI), and the last three related to the manipulation check of the independent variable (perceived interest in performing the task). All questions were assessed using a 7-point Likert scale, except for the last scale (manipulation check of the independent variable), which is a bipolar semantic scale.
The first scale, related to moderator 1, is derived from the prevalidated scale by Yun et al. (2007). The Self-enhancement motive was operationalized, according to Yun et al.'s (2007) study, as an individual employee's sensitivity to other people's perception of him or her and the employee's level of motivation to adapt his or her behavior in order to project a good self-image to others. During their study, they validated a six-item scale that has also been employed as the measure for this study.
The second scale, related to moderator 2, is derived from the prevalidated scale by Parker (1998). The Self-efficacy motive was operationalized, following Parker's (1998) directives, as people's belief in their capability to perform such a task if it were asked of them, not whether they actually carried out the particular task. The items selected for this scale were judged to be the most generalizable to other organizations. In fact, the set of tasks was not intended to be exhaustive but a representation of an expanded role that applies across jobs and hierarchical levels (Parker, 1998).
The third scale, related to the dependent variable, is derived from Noy and Zhang (2023)' analysis of job satisfaction and self-efficacy.
The fourth scale, related to the manipulation check X, is derived from the prevalidated scale by Sprott et al. (2009).
All the scales were adapted based on the needs of the experimental research.
Finally, the fourth and last part of the questionnaire is characterized by the block dedicated to demographic questions, where respondents were asked about their gender and age.

3.2 Results

3.2.1 Data analysis

The data collected through the questionnaire provided by the survey generated on Qualtrics XM was exported to the SPSS (Statistical Package for Social Science) software for analysis. Initially, I decided to perform an exploratory factor analysis to analyze and validate the items of the scales used in the conceptual model in the experimental research. Specifically, a principal component analysis was conducted as the extraction method, applying Varimax as the rotation technique. To decide how many factors to extract, the total variance explained table was examined, verifying that according to the Kaiser rule, the eigenvalues were greater than 1 and that the cumulative percentage variance was over 60%. Additionally, the communalities table and the component matrix were observed. Specifically, all items had an extraction value greater than 0.5 and a loading score higher than 0.3. Therefore, it was decided to retain all the items that make up the scales, thereby validating them.

After validating all the scales, a reliability test was conducted to verify the reliability level of the validated scales. In particular, the Cronbach's alpha value of the constructs was observed, ensuring it was above 0.60. For the first moderator's scale, a value of 0.948 was found; for the second moderator's scale, a value of 0.939 was recorded; for the third scale of the dependent variable, a value of 0.969 emerged; while for the manipulation check scale of the independent variable, a value of 0.961 was found. Therefore, all the scales proved to be reliable.

Additionally, the KMO test for the measure of sampling adequacy was performed. For the first moderator's scale, a value of 0.730 was found; for the second moderator's scale, a value of 0.758 was recorded; for the third scale of the dependent variable, a value of 0.768 emerged; while for the manipulation check scale of the independent variable, a value of 0.781 was found. Therefore, in all cases, the level of adequacy was more than adequate (>0.6). Subsequently, Bartlett's test of sphericity was conducted, which proved to be statistically significant, with all cases showing a p-value of 0.001 (p-value $< \alpha = 0.05$).

3.2.2 Hypotheses results

After conducting both the factor analyses and the reliability tests, the main hypotheses of the conceptual research model were examined to confirm or reject their statistical significance and, consequently, their success.

H1

To verify the significance of the direct hypothesis (H1), a comparison of means was conducted using a One-Way ANOVA to test the effect of the independent variable (Type of Task: routine vs. non-routine) on the dependent variable (perception of being augmented by Generative AI). Specifically, the independent variable (X) is categorical nominal in nature and is divided into two different conditions coded as 0 (non-routine task) and 1 (routine task), while the dependent variable (Y) is continuous metric in nature.

After performing the ANOVA, by observing the descriptive statistics table, it was noted that the group of respondents exposed to the scenario coded as 0 (85 people) had a mean of 2.5373, while those exposed to a visual condition labeled as 1 (89 people) had a mean value of 5.4944. Additionally, considering the ANOVA table, a p-value for the F-test of 0.001 was found, which was statistically significant (p-value < α = 0.05). Therefore, it was possible to observe a statistically significant difference between the group means, thus confirming the effect of X on Y. Hence, the direct hypothesis H1 (Main effect) was demonstrated.

H2A

To verify the significance of the moderation hypothesis (H2A), a comparison of means was conducted using a Two-Way ANOVA to test the joint interaction effect between the independent variable (Type of Task: routine vs. non-routine) and the first moderating variable (self-enhancement) on the dependent variable (perception of being augmented by Generative AI). Specifically, the independent variable (X) and the moderating variable (W1) are categorical nominal in nature and are both divided into two different conditions coded as 0 (non-routine task; low level of self-enhancement) and 1 (routine task; high level of self-enhancement), while the dependent variable (Y) is continuous metric in nature.

After performing the ANOVA, by observing the descriptive statistics table, it was noted that the group of respondents exposed to the scenario coded as 0,0 (29 people) had a mean of 3.4598, those exposed to a visual condition labeled as 0,1 (56 people) had a mean value of 2.0595, individuals who viewed the visual stimulus coded as 1,0 (39 people) reported a mean of 4.5983, while subjects who saw the scenario labeled as 1,1 (50 people) expressed a mean value of 6.1933. Additionally, considering the test of between-subjects effects table, a p-value for the corrected model of 0.001 was found, which is statistically significant (p-value < α = 0.05). Subsequently, all the effects of the independent variables (X, W1, and X*W1) on the dependent variable (Y) were examined. For the first direct effect between X and Y, a p-value of 0.001 was found. For the second direct effect between W1 and Y, a p-value of 0.281 was found. Regarding the joint interaction effect between X and W1 on Y, a p-value of 0.001 was found. Therefore, a statistically significant difference was observed between the group means, thus confirming the joint effect between X and W1 on Y. Hence, the moderation hypothesis H2A (Interaction effect 1) was demonstrated.

H2B

To verify the significance of the moderation hypothesis (H2B), a comparison of means was conducted using a Two-Way ANOVA to test the joint interaction effect between the independent variable (Type of Task: routine vs. non-routine) and the second moderating variable (self-efficacy) on the dependent variable (perception of being augmented by Generative AI). Specifically, the independent variable (X) and the moderating variable (W2) are categorical nominal in nature and are both divided into two different conditions coded as 0 (non-routine task; low level of self-efficacy) and 1 (routine task; high level of self-efficacy), while the dependent variable (Y) is continuous metric in nature.

After performing the ANOVA, by observing the descriptive statistics table, it was noted that the group of respondents exposed to the scenario coded as 0,0 (36 people) had a mean of 3.4259, those exposed to a visual condition labeled as 0,1 (49 people) had a mean value of 1.8844, individuals who viewed the visual stimulus coded as 1,0 (43 people) reported a mean of 4.5891, while subjects who saw the scenario labeled as 1,1 (46 people) expressed a mean value of 6.3406. Additionally, considering the test of between-subjects effects table, a p-value for the corrected model of 0.001 was found, which is statistically significant (p-value $< \alpha = 0.05$). Subsequently, all the effects of the independent variables (X, W2, and X*W2) on the dependent variable (Y) were examined. For the first direct effect between X and Y, a p-value of 0.001 was found. For the second direct effect between W2 and Y, a p-value of 0.114 was found. Regarding the joint interaction effect between X and W2 on Y, a p-value of 0.001 was found. Therefore, a statistically significant difference was observed between the group means, thus confirming the joint effect between X and W2 on Y. Hence, the moderation hypothesis H2B (Interaction effect 1) was demonstrated.

Chapter 4 - Conclusion

The research gap addressed with this research can help to contribute towards academic progress regarding the use of Generative AI tools and the people's perception of being augmented by the use of them. In particular, analysing the effect of different type of tasks and human agency motives. By doing so, the research could also be useful for companies for understanding workers' adherence of Artificial Intelligence instruments.

4.1 Academic contributions

The recent advancements in Generative Artificial Intelligence have spread new fears among people, especially workers that see the future of their jobs uncertain. As aforementioned, Generative AI tools are capable now to replicate many tasks and there has been particular attention to their ability to create writing assignments with an extremely good quality and in really fast times (Brynjolfsson et al., 2023; Noy and Zhang, 2023). The existing literature had focused the research on analyzing whether the productivity of certain workers might be improved by using Generative AI tools and how the collaboration between human and Generative Artificial Intelligence leads to more efficiency for many industries (Dell'acqua et al., 2023; Noy and Zhang, 2023; Brynjolfsson et al., 2023). Although, this study aimed to discover the perception that workers might have while working with Generative AI tools. In fact, while might be easy to understand that these new technologies represent now the new frontier for many types of work it is still vague how people will adapt to this new life. The results of this experimental study highlighted that people see the possibility of delegating monotonous tasks to Generative AI tools as an augmentation and result feeling empowered. This outcome confirms what has already been discussed by Puntoni et al. (2020) that analyzed the feeling of empowerment that consumers may experience when delegating to Artificial Intelligence some tasks and gain then time for more satisfactory and meaningful activities. Also, regarding the work sphere, Noy and Zhang (2023) tested that the job satisfaction of their respondents substantially increased after using ChatGPT.
Another fundamental discovery that helps that existing literature regarding Artificial Intelligence, but more specifically Generative Artificial Intelligence, is the moderating role of two distinct human motives: the Self-enhancement motive and the self-efficacy motive. In fact, here it has been proved that respondents who resulted high in self-enhancement and self-efficacy felt more the augmentation due to the delegation of routine tasks to Generative AI tools. This outcome is aligned with Yun et al. (2007) research that pointed out that workers with high self-enhancement motive are more prone to want to improve their performances, because it would directly impress both their colleagues and managers. And given the increase in productivity with the use of

generative AI tools (Noy and Zhang, 2023), it is understandable why these subjects are attracted by this new technology.

Regarding the other agentic motive, self-efficacy, the fact that people that resulted high in this factor felt a stronger perception of augmentation strengthens Lent and et al. (1987)'s belief that people that feel capable of performing well particular tasks will cope more successfully with change. It also aligns with the possibility predicted by Cannon and Rucker (2022) that self-efficacy motive may lead to a heightened focus on personal success, goal that perfectly explains why the use of Generative AI, that is capable of improving efficiency and relieving workload, is seen as an augmentation.

On the other hand, an interesting result of this study is the negative effect of delegating a non-routine task to Generative AI tools. In fact, according to Mertens and Romeu-Gordo (2023) routine tasks, unlike non-routine ones, are more likely automated by computerization due to their nature, activities that can be accomplished by following explicit rules (Autor et al., 2003). In addition, the feeling of empowerment that someone may gain from delegating some tasks is easily overturned when the person loses the sense of accomplishment related to an activity (Moon and Nass, 1998).

4.2 Managerial contributions

This study inspects the effect of agentic motives, specifically self-enhancement and self-efficacy, on workers' perception of being augmented by Generative AI tools for routine and non-routine tasks. Companies may find this study useful to raise their awareness regarding the adoption of Generative AI tools, and how important is to understand workers' necessity of accomplishment when working.

First, Generative artificial intelligence tools can help organizations increase productivity. By eliminating routine tasks, employees can focus on more complex and challenging tasks, leading to an increase in job satisfaction.

Then, it could be important for companies to analyze employees' motivation so that it could be easier to understand how the worker will cope with the introduction of new technologies. In case of low levels of agentic motives, training courses might help the development of the organizations.

4.3 Limitations and future directions

The findings of this study should be interpreted in the light of several limitations.

Firstly, the results come from a limited sample of participants without any kind of distinction between them. Future research may focus on more specific groups of people, such as a study that compare the results of the perception of being augmented by Generative AI tools between males and females. In fact, it was proven before that gender role influences on technology self-efficacy (Huffman et al., 2013), and this may lead to different result regarding the effect that the self-efficacy motive has on the perception of being augmented by Generative AI tools for routine e non-routine tasks.

Second, the current research considered two tasks that emerged from a qualitative analysis that was conducted between marketing workers between the age of 23 and 27. Future research may find new scenarios so that people that work in different areas may empathize with more.

More, a limitation of this study can be the fact that there was no age restriction. Since the research focuses on the use of a new technology, a distinction between the different generations might be interesting.

Lastly, the experimental study was conducted through a questionnaire. The quantitative method was functional for the purpose of this study but can represent a limitation for the analysis of the psychological motives of the respondents. Further research may take into consideration a qualitative approach for the inspection of people's perceptions regarding Generative Artificial Intelligence.

Nonetheless, the sample results provide some intriguing insights for further research and should be further explored in the future.

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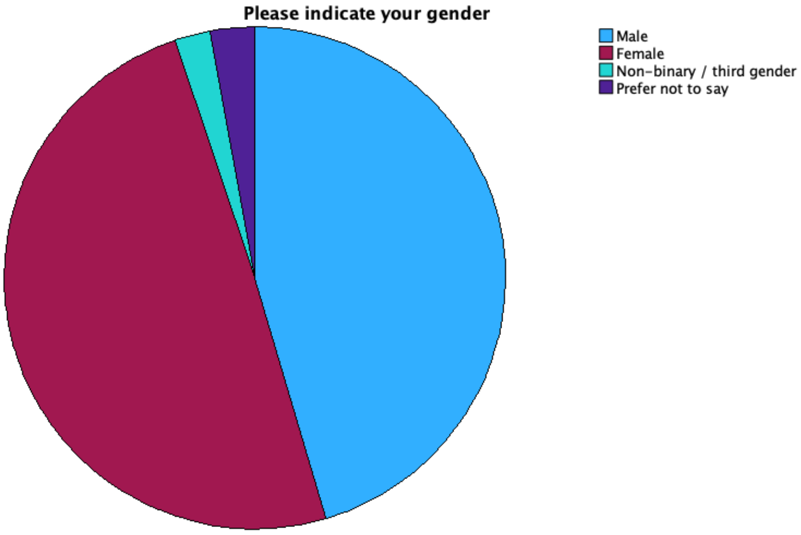
Appendices

Appendix main test

Descriptive statistics: age

Please indicate your gender

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	Male	79	45.4	45.4	45.4
	Female	86	49.4	49.4	94.8
	Non-binary / third gender	4	2.3	2.3	97.1
	Prefer not to say	5	2.9	2.9	100.0
	Totale	174	100.0	100.0	

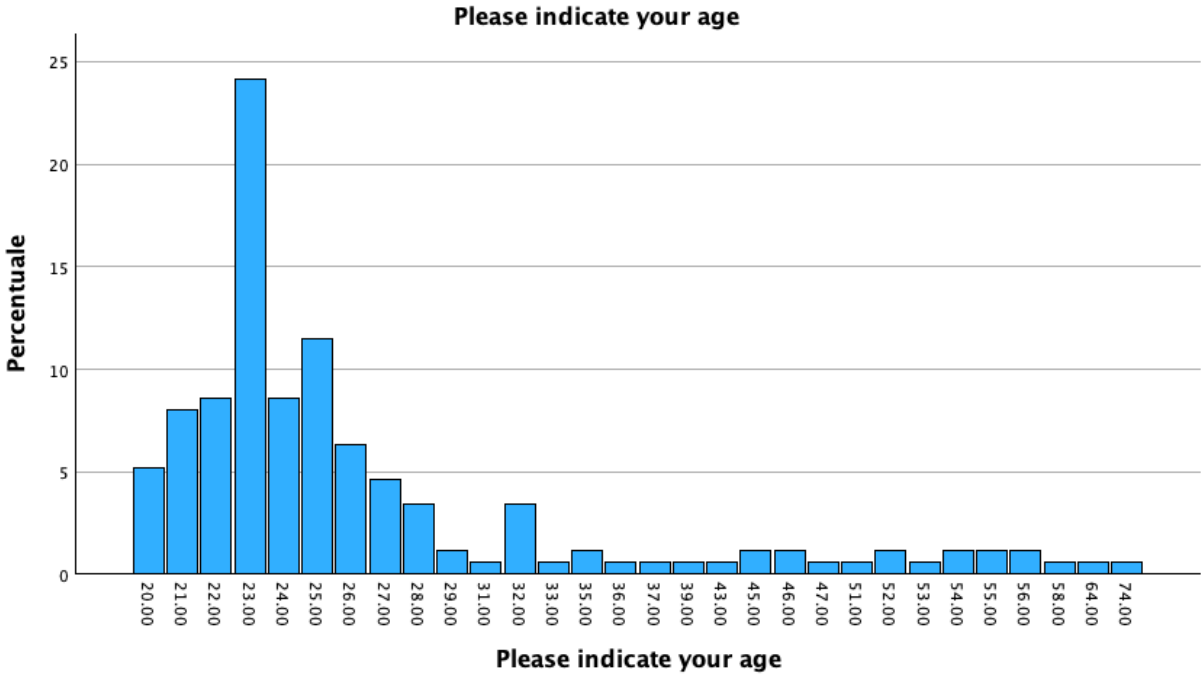


Descriptive statistics: gender

Statistiche

Please indicate your age

N	Valido	174
	Mancante	0
Media		27.5977
Mediana		24.0000
Modalità		23.00
Deviazione std.		9.79555
Varianza		95.953
Intervallo		54.00
Minimo		20.00
Massimo		74.00



Factorial analysis: first moderator

Varianza totale spiegata

Componente	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	2.717	90.563	90.563	2.717	90.563	90.563
2	.212	7.072	97.635			
3	.071	2.365	100.000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. – It is important to me to give a good impression to others	1.000	.913
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. – I am sensitive to the impression about me that others have	1.000	.945
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. – I try to create the impression that I am a "good" person to others	1.000	.859

Metodo di estrazione: Analisi dei componenti principali.

Matrice dei componenti[a]

	Componente 1
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. – It is important to me to give a good impression to others	.956
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. – I am sensitive to the impression about me that others have	.972
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. – I try to create the impression that I am a "good" person to others	.927

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		.730
Test della sfericità di Bartlett	Appross. Chi-quadrato	547.184
	gl	3
	Sign.	<.001

Reliability Test: first moderator

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
.948	.948	3

Factorial analysis: second moderator

Varianza totale spiegata

	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
Componente	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	2.675	89.168	89.168	2.675	89.168	89.168
2	.202	6.718	95.886			
3	.123	4.114	100.000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I feel confident representing my work in meetings with senior management	1.000	.888
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I feel confident making suggestions to management about ways to improve the working of my section	1.000	.917
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I feel confident contributing to discussions about the company's strategy	1.000	.870

Metodo di estrazione: Analisi dei componenti principali.

Matrice dei componenti[a]

	Componente 1
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I feel confident representing my work in meetings with senior management	.942
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I feel confident making suggestions to management about ways to improve the working of my section	.958
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I feel confident contributing to discussions about the company's strategy	.933

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		.758
Test della sfericità di Bartlett	Appross. Chi-quadrato	463.848
	gl	3
	Sign.	<.001

Reliability Test: second moderator

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
.939	.939	3

Factorial analysis: dependent variable

Varianza totale spiegata

Componente	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	2.835	94.489	94.489	2.835	94.489	94.489
2	.115	3.831	98.320			
3	.050	1.680	100.000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I think Generative AI improves my performance	1.000	.954
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I feel empowered by using Generative AI	1.000	.958
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I enjoy to delegate the task that I saw before to generative AI	1.000	.923

Metodo di estrazione: Analisi dei componenti principali.

Matrice dei componenti[a]

	Componente 1
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I think Generative AI improves my performance	.977
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I feel empowered by using Generative AI	.979
Indicate on a scale of 1 (completely disagreeing) to 7 (fully agreeing) to what extent you agree or disagree with the following statements. - I enjoy to delegate the task that I saw before to generative AI	.961

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		.768
Test della sfericità di Bartlett	Appross. Chi-quadrato	703.388
	gl	3
	Sign.	<.001

Reliability Test: dependent variable

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
.969	.971	3

Factorial analysis: manipulation check independent variable

Varianza totale spiegata

Componente	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	2.788	92.932	92.932	2.788	92.932	92.932
2	.115	3.818	96.749			
3	.098	3.251	100.000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Indicate on a scale of 1 to 7 to what extent you have perceived the textual stimulus read earlier - Tedious:Interesting	1.000	.932
Indicate on a scale of 1 to 7 to what extent you have perceived the textual stimulus read earlier - Unstimulating:Stimulating	1.000	.932
Indicate on a scale of 1 to 7 to what extent you have perceived the textual stimulus read earlier - Monotonous:Exciting	1.000	.923

Metodo di estrazione: Analisi dei componenti principali.

Matrice dei componenti[a]

	Componente 1
Indicate on a scale of 1 to 7 to what extent you have perceived the textual stimulus read earlier - Tedious:Interesting	.965
Indicate on a scale of 1 to 7 to what extent you have perceived the textual stimulus read earlier - Unstimulating:Stimulating	.966
Indicate on a scale of 1 to 7 to what extent you have perceived the textual stimulus read earlier - Monotonous:Exciting	.961

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		.781
Test della sfericità di Bartlett	Appross. Chi-quadrato	593.837
	gl	3
	Sign.	<.001

Reliability Test: manipulation check independent variable

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
.961	.962	3

One-Way ANOVA (X-Y)

Descrittive

DV

	N	Medio	Deviazione std.	Errore std.	95% di intervallo di confidenza per la media		Minimo	Massimo
					Limite inferiore	Limite superiore		
.00	85	2.5373	.93449	.10136	2.3357	2.7388	1.00	4.00
1.00	89	5.4944	.92947	.09852	5.2986	5.6902	3.67	7.00
Totale	174	4.0498	1.74960	.13264	3.7880	4.3116	1.00	7.00

ANOVA

DV

	Somma dei quadrati	df	Media quadratica	F	Sig.
Tra gruppi	380.189	1	380.189	437.762	<.001
Entro i gruppi	149.379	172	.868		
Totale	529.568	173			

Two-Way ANOVA (X-W1-Y)

Statistiche descrittive

Variabile dipendente: DV

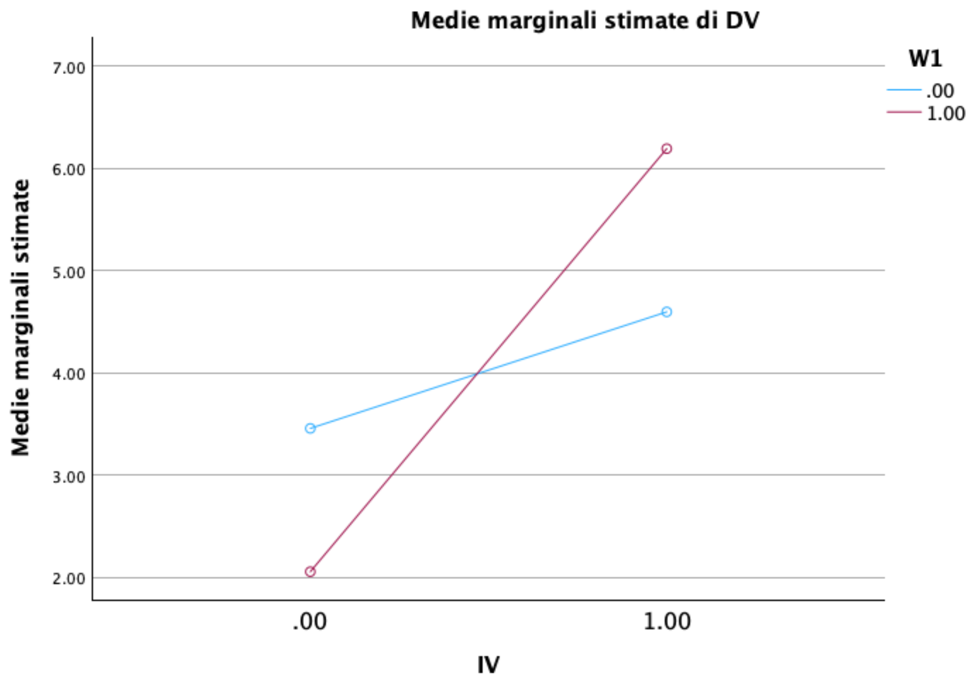
IV	W1	Medio	Deviazione std.	N
.00	.00	3.4598	.16460	29
	1.00	2.0595	.79926	56
	Totale	2.5373	.93449	85
1.00	.00	4.5983	.24399	39
	1.00	6.1933	.60643	50
	Totale	5.4944	.92947	89
Totale	.00	4.1127	.60570	68
	1.00	4.0094	2.19208	106
	Totale	4.0498	1.74960	174

Test di effetti tra soggetti

Variabile dipendente: DV

Origine	Somma dei quadrati di tipo III	df	Media quadratica	F	Sig.
Modello corretto	473.393[a]	3	157.798	477.530	<.001
Intercetta	2715.284	1	2715.284	8217.053	<.001
IV	283.703	1	283.703	858.548	<.001
W1	.387	1	.387	1.172	.281
IV * W1	91.566	1	91.566	277.100	<.001
Errore	56.176	170	.330		
Totale	3383.333	174			
Totale corretto	529.568	173			

a. R-quadrato = .894 (R-quadrato adattato = .892)



Two-Way ANOVA (X-W2-Y)

Statistiche descrittive

Variabile dipendente: DV

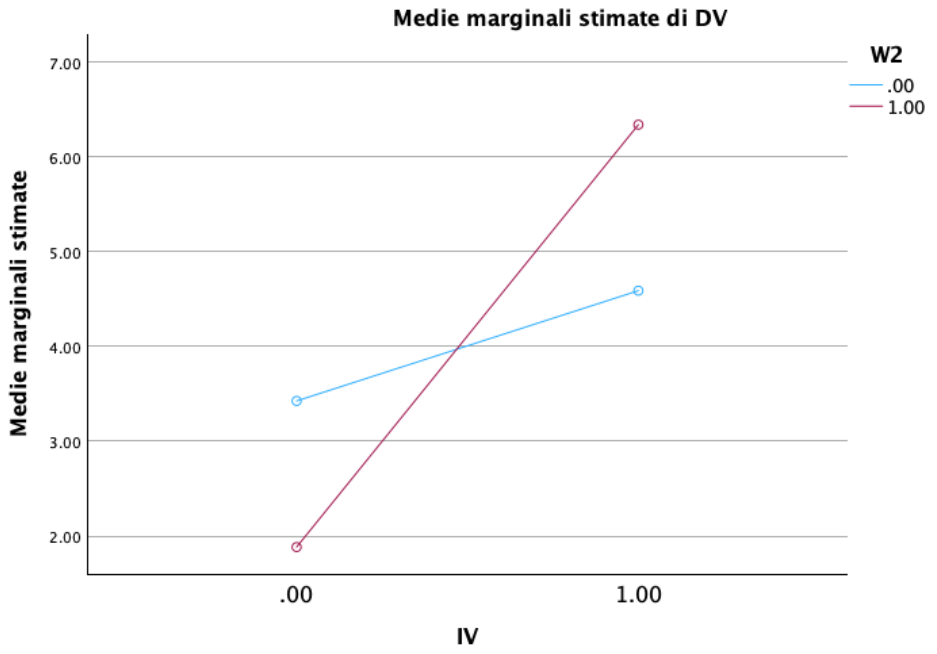
IV	W2	Medio	Deviazione std.	N
.00	.00	3.4259	.23382	36
	1.00	1.8844	.67888	49
	Totale	2.5373	.93449	85
1.00	.00	4.5891	.23946	43
	1.00	6.3406	.34776	46
	Totale	5.4944	.92947	89
Totale	.00	4.0591	.62875	79
	1.00	4.0421	2.30338	95
	Totale	4.0498	1.74960	174

Test di effetti tra soggetti

Variabile dipendente: DV

Origine	Somma dei quadrati di tipo III	df	Media quadratica	F	Sig.
Modello corretto	497.682[a]	3	165.894	884.454	<.001
Intercetta	2830.385	1	2830.385	15090.026	<.001
IV	338.891	1	338.891	1806.778	<.001
W2	.473	1	.473	2.520	.114
IV * W2	116.375	1	116.375	620.444	<.001
Errore	31.886	170	.188		
Totale	3383.333	174			
Totale corretto	529.568	173			

a. R-quadrato = .940 (R-quadrato adattato = .939)



Summary

Chapter 1 – Implications of Generative AI in the workplace and individual experience: a psychological and sociological perspective

The rapid development of artificial intelligence (AI) systems has increasingly integrated AI into everyday life, especially with the advent of Generative AI, which includes technologies capable of generating new content such as text, images, and audio (Feuerriegel et al., 2023). Notable examples include GPT-4, DALL-E, and Copilot, which are transforming work and communication (Brynjolfsson et al., 2023). This study focuses on large language models (LLMs) based on the Transformer architecture, which learn from extensive datasets to generate outputs without specific instructions (Bubeck et al., n.d.; Vaswani et al., 2017). Four main factors drive the advancements in generative AI: computing scale, model architecture innovations, pre-training with large amounts of data, and refined training techniques (Kaplan et al., 2020; Liu et al., 2023; Patel & Wong, 2023).

Generative AI's relevance extends beyond technological achievements to significant sociological impacts, including potential GDP increases and job displacement (Goldman Sachs, 2023). The concept of human-AI collaboration dates back to Licklider's (1960) "man-computer symbiosis," evolving into modern centaur systems where AI complements human intelligence (Agni Orfanoudaki et al., 2022). These collaborations raise questions about identity, reward allocation, and the future of the workforce (Cantrell et al., 2022; Thompson, 2022).

Generative AI's impact on jobs involves a dual potential of augmentation and replacement, affecting industries such as healthcare, marketing, and education (Davenport et al., 2018; Ma & Sun, 2020; Obermeyer et al., 2019). While some fear job displacement (Ford, 2015; West, 2018), others see AI enhancing productivity and work experiences (McKinsey Global Institute, 2017; Noy & Zhang, 2023). However, limitations such as hallucinations, data quality issues, and lack of model explainability remain challenges (Azamfirei et al., 2023; Ji et al., 2023; Nah et al., 2023).

Ethical concerns in AI include harmful content, bias, over-reliance, misuse, data privacy, and the digital divide (Brundage et al., 2020; Siau & Wang, 2020; Van Dijk, 2006).

Addressing these issues requires robust policies, inclusive access to AI technology, and comprehensive training (Nah et al., 2023).

Generative AI can enhance worker satisfaction by allowing them to focus on meaningful tasks, thus enhancing self-efficacy and job satisfaction (Botti & McGill, 2011; Fishback & Choi, 2012; Huffman et al., 2013). Conversely, it may create a sense of replacement, impacting self-worth and efficacy (Moon & Nass, 1998; Puntoni et al., 2020; Seabrook, 2019).

Human agency, driven by self-efficacy and self-enhancement, influences behavior in the workplace (Abele et al., 2007; Bandura, 1982; Cannon & Rucker, 2022). High self-efficacy leads to positive engagement and resilience, while self-enhancement motivates behaviors to improve self-image (Yun et al., 2007). However, gaps in the literature remain, particularly regarding the link between AI augmentation and agentic motives (Cannon & Rucker, 2022).

This study investigates the impact of Generative AI on workers' perceptions of augmentation, focusing on routine versus non-routine tasks and the moderating roles of self-efficacy and self-enhancement.

To address this issue, the research question is formulated as follows:

"To what extent do self-efficacy and self-enhancement motives influence workers' perceptions of being augmented by Generative AI in their roles?"

Chapter 2 – Conceptual framework and Hypotheses development

This chapter outlines the conceptual framework and development of hypotheses regarding the impact of Generative AI on workers' perceptions of being augmented, focusing on routine versus non-routine tasks. The moderating roles of self-enhancement and self-efficacy are also explored.

2.1 Routine and Non-routine Tasks on Workers' Perception of Being Augmented by Generative AI

Previous research has shown that computerization affects different categories of tasks in various ways (Autor et al., 2003). The advent of powerful generative AI tools has

reignited discussions about automation (Noy & Zhang, 2023), with some studies claiming that automation displaces workers and increases unemployment (Acemoglu & Restrepo, 2018). Conversely, other studies suggest that automation complements workers and enhances productivity (Agrawal et al., 2019).
In this study, a qualitative survey was conducted with 44 participants to understand their experiences with generative AI in the workplace. Participants described situations where they felt augmented by AI tools, with most examples involving routine tasks. Routine tasks are defined as limited, well-defined activities that follow explicit rules (Autor et al., 2003) and are more susceptible to automation (Mertens & Romeu-Gordo, 2023). Previous findings suggest that generative AI, like ChatGPT, increases job satisfaction by automating tedious components or allowing faster task completion (Noy & Zhang, 2023). This research aims to determine if using generative AI for routine tasks is more likely to make workers feel augmented than using it for non-routine tasks.

H1: Routine tasks (vs. non-routine tasks) will positively (vs. negatively) impact workers' perception of being augmented by Generative AI tools.

2.2 The Moderating Role of Human Agency

Research indicates that impression management is common in the workplace (Wayne & Liden, 1995). High-performing employees are valued and likely to be rewarded, which motivates them to enhance their self-image by improving performance (Yun et al., 2007). Noy and Zhang's (2023) study confirmed that generative AI improves productivity but does not eliminate the fear of replacement.
This study investigates the conditions under which workers feel augmented by generative AI, particularly focusing on self-enhancement. It hypothesizes that individuals with a high level of self-enhancement are more likely to view generative AI as a tool that augments their capabilities and performance.

H2: A high level of self-enhancement will positively moderate the relationship between routine tasks and workers' perception of being augmented by Generative AI tools. Specifically, high levels (vs. low levels) of self-enhancement will make workers feel more *augmented by routine tasks (vs. non-routine tasks).*

According to Bandura (1986), individuals with high achievement goals are more likely to self-monitor and sustain efforts toward satisfactory solutions. When knowledge and skills are lacking, a sense of self-efficacy motivates individuals to improve their competence (Schunk, 1995). Therefore, it is expected that workers with high self-efficacy will perceive themselves as augmented rather than replaced when using generative AI.

H3: A high level of self-efficacy will positively moderate the relationship between routine tasks and workers' perception of being augmented by Generative AI tools. Specifically, high levels (vs. low levels) of self-efficacy will make workers feel more augmented by routine tasks (vs. non-routine tasks).

Chapter 3 – Experimental research

This chapter presents the methodological approach and results of the experimental research conducted to investigate the impact of Generative AI on workers' perceptions of being augmented, focusing on routine versus non-routine tasks and the moderating roles of self-enhancement and self-efficacy.

3.1 Methodological Approach

3.1.1 Methodology and Study

This experimental study employed a 2x2 between-subjects design to investigate the effects of task type (routine vs. non-routine) on workers' perceptions of being augmented by Generative AI. The data was collected through a self-administered survey conducted in Italy in May 2024 using the Qualtrics XM platform. A non-probabilistic convenience sampling method was used, targeting respondents of all ages and genders, as demographic variables were not expected to significantly influence the results.

3.1.2 Participants and Sampling Procedure

The survey was distributed to 200 individuals, with 174 fully participating by completing all questions. The remaining 26 incomplete responses were discarded during data cleaning. Participants were contacted through an anonymous link sent via instant messaging and social media networks (WhatsApp and Instagram). The sample primarily included graduating university students and recent hires across various Italian cities, with an average age of 27.59 years (range 20-74). The gender distribution was 49.4% female, 45.4% male, and 5.2% non-binary or undisclosed.

3.1.3 Data Collection and Questionnaire Composition

The questionnaire consisted of 14 questions (12 specific and 2 demographic) and was divided into four main parts:

1. Introduction: Explained the academic purpose and ensured privacy compliance.
2. Randomized Block of Scenarios: Two immersive texts depicting routine and non-routine tasks involving Generative AI. Randomization ensured equal exposure to both stimuli, avoiding cognitive biases.
3. Main Questions: Twelve questions assessing self-enhancement, self-efficacy, perception of being augmented by Generative AI, and manipulation check of task interest. Responses were measured using a 7-point Likert scale, except for the manipulation check, which used a bipolar semantic scale.
4. Demographic Questions: Collected information on gender and age.

The scales used were derived from prevalidated sources:

- Self-enhancement: Yun et al. (2007)
- Self-efficacy: Parker (1998)
- Perception of being augmented: Noy and Zhang (2023)
- Manipulation check: Sprott et al. (2009)

All scales were adapted for the study's specific needs.

3.2 Results

3.2.1 Data Analysis

The collected data was exported to SPSS for analysis. An exploratory factor analysis (principal component analysis with Varimax rotation) was conducted to validate the scales. Factors with eigenvalues greater than 1 and cumulative variance over 60% were retained. All items had extraction values above 0.5 and loading scores higher than 0.3, validating the scales. Reliability tests showed Cronbach's alpha values above 0.60 for all constructs, confirming their reliability. The KMO test indicated adequate sampling adequacy, and Bartlett's test of sphericity was statistically significant ($p < 0.05$).

3.2.2 Hypotheses Results

The main hypotheses were tested using One-Way and Two-Way ANOVA analyses.

H1: Direct Effect of Task Type on Perception of Augmentation
A One-Way ANOVA tested the effect of task type (routine vs. non-routine) on perception of being augmented by Generative AI. Results showed a significant difference between group means, confirming the direct hypothesis H1 ($p = 0.001$).

H2A: Moderation by Self-enhancement
A Two-Way ANOVA tested the interaction effect between task type and self-enhancement. The analysis indicated a significant joint effect, confirming the moderation hypothesis H2A ($p = 0.001$).

H2B: Moderation by Self-efficacy
A Two-Way ANOVA tested the interaction effect between task type and self-efficacy. The analysis indicated a significant joint effect, confirming the moderation hypothesis H2B ($p = 0.001$).

Chapter 4 - Conclusion

This chapter presents the conclusion of the study, discussing the academic and managerial contributions, as well as the limitations and future directions for research on the impact of Generative AI on workers' perceptions of being augmented, focusing on routine versus non-routine tasks and the moderating roles of self-enhancement and self-efficacy.

4.1 Academic Contributions

This research addresses a significant gap in the academic literature regarding the use of Generative AI tools and workers' perceptions of being augmented. By analyzing the effect of different types of tasks and human agency motives, this study contributes to a deeper understanding of how workers adapt to Generative AI. The findings highlight that delegating monotonous tasks to Generative AI tools is perceived as augmentation, leading to feelings of empowerment, which supports the work of Puntoni et al. (2020) and Noy and Zhang (2023). Moreover, the study identifies the moderating roles of self-enhancement and self-efficacy, showing that individuals with higher levels of these motives feel more augmented by Generative AI, aligning with research by Yun et al. (2007), Lent et al. (1987), and Cannon and Rucker (2022). Additionally, the negative perception of delegating non-routine tasks to AI tools aligns with Mertens and Romeu-Gordo (2023) and Moon and Nass (1998).

4.2 Managerial Contributions

This study provides valuable insights for organizations regarding the adoption of Generative AI tools. Companies can use these findings to enhance productivity by eliminating routine tasks and allowing employees to focus on more complex and satisfying tasks, thereby increasing job satisfaction. Understanding employees' motivations, particularly self-enhancement and self-efficacy, can help organizations better manage the introduction of new technologies. Training programs can be developed to enhance these motives, aiding workers in coping with technological changes.

4.3 Limitations and Future Directions

Several limitations should be considered when interpreting the findings of this study. The sample size was limited, and future research could focus on specific demographic groups, such as comparing the perceptions of males and females, considering the influence of gender on technology self-efficacy (Huffman et al., 2013). Additionally, the study's scenarios were based on qualitative analysis of marketing workers aged 23-27, suggesting a need for broader scenarios applicable to different industries. Age restrictions were not applied, and future studies could investigate generational differences in the perception of Generative AI. Finally, the use of a questionnaire, while functional, limits the depth of psychological insights. Future research could employ qualitative methods to explore perceptions of Generative AI in greater detail.

Despite these limitations, the study provides intriguing insights and a foundation for future research in the field of Generative AI and human-technology interaction.