Generative AI across the Corporate Hierarchy: The Disparity of Emotions, Attitudes, Social Norms and Usage

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Abstract

Organizations can unlock numerous benefits by using generative artificial intelligence (AI). Thus, understanding the predictors driving its usage is crucial. Psychological factors such as emotions, attitudes, and norms play a key role. Research has examined these for employees and leaders separately; however, without comparing them across the hierarchy. This is important as research has discovered hierarchical differences in these factors regarding several organizational phenomena, such as digital readiness. Disparities may result in disregarded concerns, leading to a decline in trust and motivation. Building on identity theory, we examine differences in emotions, attitudes, and norms toward generative AI across the hierarchy. Our results show that high-level employees exhibit more excitement, less perceived threat, and stronger norms, yet this does not translate into higher usage. This study highlights the risk of leaders falling into impression management, given their low usage rates, and warns against disconnected levels based on discrepancies in psychological factors.

Keywords: Generative Artificial Intelligence, Emotions, Attitudes, Social Norms, Hierarchical Differences.

1. Introduction

Using generative AI technologies unlocks several beneficial outcomes for organizations, including productivity improvements (Noy & Zhang, 2023; Brynjolfsson et al., 2023; Peng et al., 2023) and higher market valuations (Babina et al., 2024). Prior research has revealed that AI benefits develop incrementally (Brock & Von Wangenheim, 2019). Mainly through the automation of business processes (Collins et al., 2021; Davenport & Ronanki, 2018), but also through the enhancement of analytical thinking, creativity and writing skills (Dell'Acqua et al., 2023). Therefore, achieving high usage rates is crucial for organizations, but largely depends on the individual decision of each employee.

Extensive research has analyzed the factors driving technology usage under diverse conditions. Various studies attribute importance to psychological factors, such as emotions, attitudes, and perceived social norms across different information technologies (Venkatesh & Davis, 2000; Marangunić & Granić, 2015; Blut et al., 2022). Thereby, the studies consistently attribute relevance to these psychological factors regardless of the technology considered. For the particular field of AI and generative AI, recent studies support the applicability of emotions, attitudes and perceived social norms as driving factors for its usage (Rahman et al., 2023; Kelly et al., 2023, Ivanov et al., 2024). For instance, empirical results indicate that positive attitudes and subjective norms significantly impact lecturers' and students' intention to use and adopt generative AI tools in daily tasks (Ivanov et al., 2024). Other studies highlight the important role of positive emotions during the adoption process of generative AI technologies (Gupta & Yang, 2024). Therefore, positive emotions, attitudes and strongly perceived social norms are key for turning an employee's decision in favor of using generative AI tools.

According to Upper Echelons theory, organizations are a reflection of its top management (Hambrick & Mason, 1984). In particular, the theory suggests that psychological factors of Upper Echelons are reflected in organizational outcomes, such as the benefits achieved through using generative AI tools. This raises the question of whether psychological factors of Upper Echelons – such as emotions, attitudes, and perceived social norms – are also reflected in lower-level employees, in order to achieve these outcomes.

Extant research challenges this view and shows that top management does not generally reflect the whole organization in terms of psychological factors. Scientific studies found out that high-level employees have different emotions (Keltner et al., 2003; Van Kleef & Lange, 2020), attitudes (Treviño et al., 2008; Hornsby

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et al., 2002; Gfrerer et al., 2020), and perceptions of social norms (Burks & Krupka, 2012) about various aspects of the organization. For example, a recent study revealed that top management's attitudes toward organizational digital readiness are more positive than the attitudes of both middle- and low-level managers (Gfrerer et al., 2020). For the particular field of AI, a study found out that high-level employees are more willing to trust advice provided by AI, accept responsibility for its actions, and feel comfortable with AI monitoring and evaluating their performance compared to lower-level managers (Kolbjørnsrud et al., 2017).

Although studies have made important advancements in studying diverging emotions, attitudes, and norms across the corporate hierarchy, we still face very limited knowledge for the field of AI, generative or not.

First, previous studies have mainly examined AI emotions, attitudes, and perceived social norms of leaders (Schafheitle et al., 2021; Lee et al., 2015) and non-leaders (Cox et al., 2019; Eveslage & Nachtwei, 2023) separately, without subsequent comparison. This is important because extant studies show that employees of different hierarchical levels vary in these psychological factors, which are relevant to generative AI usage. Potentially undetected differences in emotions, attitudes and perceptions may result in a disconnection of hierarchical levels. If employees feel that their concerns are not being addressed or perceptions are disregarded, a decline in trust (Kluger & Itzchakov, 2022), and motivation (Bakker & Demerouti, 2007) can be triggered. Both variables highly correlate with team performance, which has been supported by several studies (Cerasoli et al., 2014; De Jong et al., 2016). Therefore, it is crucial for organizations to detect psychological disparities early.

Second, there is only limited empirical evidence on how emotions, attitudes, and perceived social norms toward generative AI vary across the corporate hierarchy. In particular, where these factors are more favorable or unfavorable for generative AI usage. This is important as emotions, attitudes, and perceived social norms are key factors for predicting technology usage, and therefore contribute to its usage falling short of expectations (Blut et al., 2022). The identification of negative predictors toward generative AI, enables organizations to steer available resources efficiently. Given the increased willingness to invest in generative AI in the upcoming years (Chui et al., 2023), guardrails for tailored measures are required, which provide information on priority target groups (e.g., low-level employees instead of high-level employees) and training objectives (e.g., improve attitudes rather than perceived norms).

Against this background, the present study aims to analyze potential disparities in emotions, attitudes, and social norms toward generative AI across corporate hierarchies and identify potential explanations for low usage rates.

We use identity theory to develop our hypotheses and argue that a person's role in an organizational hierarchy shapes their perceptions of identity and thereby influences emotions, attitudes, and perceptions of social norms toward generative AI. We test the hypotheses with data gained from a survey of 1,730 employees of different hierarchical levels within a multinational software company.

Our results show significant differences in generative AI emotions, attitudes, social norms, and usage rates between hierarchical levels. High-level employees experience more excitement, less threat, and stronger social norms toward generative AI compared to middle-level and low-level employees. Although the position of low-level employees is associated with more unfavorable predictors of generative AI usage, their average usage rate is the highest among all hierarchical levels and significantly higher than that of middle-level employees.

We contribute to literature examining predictors of generative AI technology usage by adding new insights into their variation across the corporate hierarchy. By identifying these significant disparities, our research not only helps companies to mitigate potential declines in trust and motivation stemming from hierarchical disconnects, but also provides guidance for designing targeted interventions, highlighting hierarchical levels with increased attention need and factors to focus on. Moreover, we extend the current literature on variations in emotions, attitudes, and social norms across organizational hierarchies by applying identity theory to the domain of generative AI. Our findings indicate that distinct identities and roles may influence emotions and perceived social norms toward generative AI between higher-level and lower-level employees. Attitudes toward generative AI may only be partially predictable based on the hierarchical level.

2. Theoretical Background

We adopt the most robust and popular definition within information systems research in this paper and define generative AI as an evolution of AI that can create and reimagine new content, as well as serve as an assistant in various domains, providing a nearly human-like aspect to its users (Strobel et al., 2024; Mondal et al., 2023).

2.1 The Importance of Emotions, Attitudes, and Social Norms for Realizing the Potential of Generative AI

The benefits of generative AI usage rank from enhancing productivity to fostering creativity (Noy & Zhang, 2023; Dell'Acqua et al., 2023). However, their realization is subject to the employee's decision to engage with the tools in suitable use cases (Mathieson, 1991). The choice to use technology is significantly driven by an individual's emotions (Beaudry & Pinsonneault, 2010), attitudes (Blut et al., 2022), and perceived social norms (Venkatesh & Morris, 2000). Most research in the field of technology usage predictors is built upon the Theory of Reasoned Action (Fishbein & Ajzen, 1975), Technology Acceptance Model and its extensions (Davis, 1989; Marangunić & Granić, 2015), as well as the Theory of Planned Behavior (Ajzen, 1991). All emphasize the importance of these factors, although to varying degrees.

Emotions: Scientific studies invoke a key role for emotions in influencing decision making (Janis & Mann, 1977; Bechara et al., 2000) and behavioral tendencies (Brockner & Higgins, 2001). Within the realm of technology usage, studies argue that emotional influences are the greatest in the early learning stages of innovations, such as the current state of generative AI technologies (Wood & Moreau, 2006). Beaudry and Pinsonneault (2010) emphasize the positive correlation between the emotion excitement and technology usage through task adaptation. Conversely, Pal et al. (2023) argue that heightened excitement fosters the usage of AI-powered conversational agents through increased intimacy and commitment. Despite differing pathways, both studies agree on excitement's positive impact on AI tool usage.

Attitudes: In psychological research, attitudes are conceptualized as an evaluative response, that predisposed one favorably or unfavorably toward performing a particular behavior (Ajzen & Fishbein, 1977; Cohen, 1990). Scientific literature posits that the perceived usefulness (Davis, 1989), trustworthiness (Balaskas et al., 2022), and threat (Martins et al., 2014; Walter & Lopez, 2008) are key determinants in shaping an individual's technology attitude and usage. A recent meta-analysis underlines the importance of the determinants (Blut et al., 2022). While the perceived threat negatively influences the intention to use generative AI (Martins et al., 2014), perceived usefulness and trustworthiness positively influence technology usage (Davis, 1989; Balaskas et al., 2022). However, their effect may differ by context, as demonstrated in the case of insurance chatbots, where trust is considered important but not as crucial as perceived usefulness for driving usage (Cardona et al., 2021).

Social norms: Social norms, dominantly defined as unwritten rules dictating behavior within a group, are pivotal in catalyzing organizational change, including the introduction of new technology (Buchanan et al., 2005; Blut et al., 2022). For instance, Belanche et al. (2019) revealed a significant impact of social norms on the intention to use AI-powered robo-advisors in FinTech, with increased influence among users with a lower level of technology familiarity.

Summarizing, a lack of excitement, unfavorable attitudes and weak social norms can be considered as a key reason for technologies usage rates, such as those of generative AI, falling behind expectations.

2.2 Reasons for Differences in Emotions, Attitudes, and Social Norms across Hierarchical Levels

"Where you sit may determine what you see" (Pratt & Rafaeli, 1997). This quote, emerging from identity research, reflects how variations in social group membership, such as an organizational hierarchy, contribute to differences in individual perceptions, associated cognition, and behavior. Identity theory (Stryker, 1980; Stryker & Serpe, 1994; Stryker, 2004) emphasizes that a person's role in a social structure shapes their perceptions of identity and thereby influences emotions (Stets, 2004), attitudes (Stryker, 2000), perceptions of social norms (Treviño et al., 2008) and behavior (Ashforth & Mael, 1989). To illustrate this theory further, Treviño et al. (2008) provide a compelling example, by arguing that senior managers view the ethics of their organization more positively than lower-level employees. Based on identity theory and social identity theory, they posit that high-ranked employees occupy different roles than lower-level employees, thus are provided with a different sense of self-meaning and influences. Due to an increased identification with the organization among senior manager, their urge to protect the organization's image as well as their own identity and image is higher. Consequently, they tend to exhibit more positive attitudes toward their organizational ethic initiatives (Treviño et al., 2008).

Anchoring identity theory to the focus of this paper, enables the following derivation of hypotheses.

Emotions and attitudes. Scientific studies discovered that individuals in senior positions exhibit greater organizational commitment compared to their lower-level colleagues (Mathieu & Zajac, 1990). Moreover, advancing within a company is closely tied to fostering strong relationships with organizational leaders, which amplifies the significance of organizationally defined identities (Weaver & Agle, 2002). Because of their strong identification with the organization and heightened organizational commitment, high-level employees tend to perceive organizational goals or initiatives, such as the introduction of generative AI technologies, more positively (Treviño et al., 2008). Consequently, this translates into a higher likelihood of positive emotions and favorable attitudes toward generative AI.

Further studies reinforce this argument, by revealing stronger concerns about the impact of AI technologies on job security among employees on lower levels of the corporate hierarchy (Ransbotham et al., 2018), as well as reduced trust in the advice provided by intelligent systems compared to top management (Kolbjørnsrud et al., 2017).

Moreover, this argument resonates with the broader view that high-level positions are associated with more positive emotions and attitudes than lower levels. Various theoretical perspectives suggest that lower positions in a social hierarchy can cause negative emotions and stress, while senior roles rather foster positive emotions and well-being. Power is often correlated with increased positive emotions, while reduced power or lower-ranking positions are associated with heightened negative emotions (Van Kleef & Lange, 2020; Keltner et al., 2003; Anderson et al., 2015). For example, a study discovered that leaders in military and government roles exhibited lower levels of stress and perceived less anxiety compared to non-leaders. These effects were particularly pronounced among powerful leaders due to their heightened sense of control (Sherman et al., 2012).

Additionally, low-level employees often identify more closely with their immediate coworkers than with the organization as a whole and its policies (Treviño et al., 2008). This strong group identification can foster a lack of excitement and attitudes that oppose the usage of generative AI to protect colleagues at the same hierarchical level (Treviño & Victor, 1992).

Given these arguments, we posit that, on average, emotions – specifically excitement –, attitudes– specifically perceptions of generative AI's usefulness, trustworthiness, and perceived threat – are less positive among lower-level employees than among high-level employees.

Hypothesis 1: Emotions toward generative AI, specifically excitement, are more positive among high-level employees than among lower-level employees.

Hypothesis 2: Attitudes toward generative AI, specifically the perceived usefulness, trustworthiness, and threat, are more positive among high-level employees than among lower-level employees.

Social norms. The strong perception of social norms is widely recognized as a predictor for technology usage (Venkatesh & Morris, 2000). Individuals who perceive expectations from coworkers, supervisors, or the organization as a whole to integrate generative AI technologies into their work are expected to exhibit higher usage rates compared to those with lower perceptions of social norms.

Studies indicate that the role of top managers is more likely to include creating and enforcing social norms within organizations. Consequently, they are more likely to perceive these norms as being actively implemented and expected from each other. Challenging this perception would not only cast doubt on the manager's self-image but also on the image of the organization (Treviño et al., 2008).

Conversely, the role of lower-level employees typically has limited involvement in the formulation of social norms and policies. They may possess less information about actual guidelines and practices compared to high-level employees. However, they are more exposed to unsupportive behaviors among their peers and supervisors (Treviño et al., 2008). Based on these arguments, we contend that high-ranked positions exhibit a stronger perception of social norms related to generative AI usage compared to lower-level employees.

Hypothesis 3: Social norms toward generative AI usage are more strongly perceived among high-level employees than among lower-level employees.

Based on the previously outlined predictive power of emotions, attitudes, and perceived social norms, combined with our hypotheses suggesting more favorable conditions in these factors among high-ranked positions, we hypothesize the following.

Hypothesis 4: Generative AI usage rates are higher among high-level employees than among lower-level employees.

To investigate these hypotheses, a study was designed which examines employees from different hierarchical levels regarding their emotions, attitudes, and perceived social norms toward generative AI. Additionally, participants indicated their generative AI usage. The next section will delve deeper into the study's methodology.

3. Method

3.1 Sample and Procedure

We sent out an online survey to all employees of a multinational software company and collected data over a 12-day period. We received 1,816 complete responses, which have subsequently been supplemented with demographic information and the hierarchical position of each respondent, sourced from the company's internal database. 95% of the sample could be matched to a hierarchical position. Hence the resulting sample for our analyses included 1,730 respondents, of which 19 respondents were on level 1 (1%), the highest hierarchical level, 192 (11%) on level 2, 721 (42%) on level 3, 528 (31%) on level 4, 226 (13%) on level 5, and 44 (2%) on level 6, the lowest hierarchical level. 70% were male participants, and 32% were over 50 years old. The first two levels were grouped as high-level employees (n = 211), levels 3 and 4 as middle-level employees (n = 1,249), and levels 5 and 6 as low-level employees (n = 270).

The group of high-level employees was composed of 80% male participants, while middle-level employees had 72% male participants, and low-level employees comprised 58% male participants. The majority of responding high-level employees was over 50 years old (62%), while middle-level employees were primarily between 41-50 years old (36%) or older (32%). Low-level employees were predominantly between 20-30 years old (49%). Respondents worked in several departments within the organization. 39% were employed in Development, 18% in Sales & Presales, and 18% in Services. The remaining respondents worked in other departments.

3.2 Measures

Dependent variables. Scales of emotions, attitudes and social norm variables were measured with a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

For emotions, we focused on excitement, which has been highlighted to be relevant for generative AI usage. Respondents were asked to rate the statement “When I think about the use of generative AI for my work, I feel excited” (Noy & Zhang, 2023).

Three different attitudes were measured and interpreted separately, namely perceived usefulness, trustworthiness and threat of generative AI. The separate analysis of the components is justified by their distinctiveness and the ambition to achieve detailed insights into which attitudes diverge and how they vary across the corporate hierarchy. This enables the formulation of specific and targeted implications. Perceived usefulness was measured with 3 items: “Using generative AI enables me to accomplish tasks more quickly”, “Using generative AI for accomplishing tasks increases my productivity”, and “Generative AI consistently produces relevant and useful outputs” (Cronbach’s alpha = .83) (Davis, 1989). Perceived trustworthiness was measured with 3 items: “Generative AI acts in my best interest”, “Ethical principles guide generative AI’s outputs”, and “I feel very confident about generative AI’s capabilities” (Cronbach’s alpha = .70). Perceived threat was measured by rating the statement “I am worried about workers in my occupation being replaced by generative AI” (Noy & Zhang, 2023).

Perceived social norms were measured with 3 items. Respondents ranked the statements “My company expects that I use generative AI for my work“, “My leaders think I should use generative AI for my work”, and “My colleagues think I should use generative AI for my work” (Cronbach’s alpha = .85) (Ajzen, 1991; Davis, 1989).

Generative AI usage was measured using a discrete scale from 0 to 100% of tasks.

Independent variable. The position of the respondents within the organization was matched from the company’s internal database through a unique identifier. The hierarchical levels were grouped into high-level, middle-level, and low-level employees.

Controls. We used *age* as control variable. Age was included because scientific studies revealed significant differences between younger and elderly users in their technology attitudes and behaviors (Charness & Boot, 2009).

4. Results

We used multivariate analysis of covariance (ANCOVA) with LSD post-hoc tests and partial eta squared (η^2) effect sizes to test the hypotheses that high-level employees differ significantly from middle- and low-level employees in their emotions, attitudes, perceptions of social norms toward generative AI, and its estimated usage.

Although homogeneity of variances was not satisfied for all dependent variables, and residuals were not normally distributed, as indicated by the Shapiro-Wilk test, research found out that ANCOVA remains valid under various non-normal distribution conditions (Blanca et al., 2017). To enhance robustness, we implemented bootstrapping (Wilcox, 2009). Further assumptions were met.

Hypothesis 1 predicted more positive emotions, specifically excitement, toward generative AI among high-level employees than among lower-level employees, which was supported (partial $\eta^2 = 0.015$, $p < 0.001$). High-level employees experienced significantly more excitement than middle-level ($p < 0.001$) and low-level employees ($p < 0.001$).

Hypothesis 2 predicted attitudes toward generative AI to be more positive among high-level employees than among lower-level employees. This was supported for the attitude perceived threat (partial $\eta^2 = 0.021$, $p < 0.001$), with significant differences between all hierarchical levels ($p < 0.001$). However, it was not supported for the attitude trustworthiness, and only partially for perceived usefulness of generative AI.

High-level employees perceived the usefulness of generative AI significantly better than middle-level employees ($p = 0.026$), however, there was no significant difference compared to low-level employees.

Hypothesis 3 predicted stronger perceptions of social norms toward generative AI among high-level employees than among lower-level employees, which was supported (partial $\eta^2 = 0.006$, $p = 0.006$). High-level employees perceived from their colleagues, leaders, and organization stronger norms toward using generative AI than middle-level ($p = 0.010$) and low-level employees ($p = 0.001$).

Hypothesis 4 predicted higher generative AI usage rates among high-level employees than among lower-level employees. This hypothesis was not supported. While significant differences between the groups were detected (partial $\eta^2 = 0.006$, $p = 0.005$), LSD analysis revealed that low-level employees exhibited significantly higher usage rates than middle-level employees ($p = 0.002$) and had the highest adjusted mean usage of all groups, although at a very low level (1.68 out of 10).

Table 1. Estimates adjusted for control variable.

Dependent variable	Hierarchy group	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	*Upper Bound*
Excitement	High	4.10	.07	3.96	4.25
	Medium	3.74	.03	3.69	3.80
	Low	3.59	.07	3.46	3.73
Usefulness	High	3.48	.06	3.36	3.60
	Medium	3.34	.02	3.29	3.39
	Low	3.41	.06	3.29	3.52
Trustworthiness	High	3.04	.06	2.92	3.15
	Medium	2.99	.02	2.95	3.04
	Low	3.01	.06	2.90	3.12
Threat	High	2.25	.08	2.08	2.42
	Medium	2.65	.03	2.59	2.72
	Low	3.00	.08	2.84	3.16
Social norms	High	3.21	.06	3.09	3.33
	Medium	3.04	.03	2.99	3.09
	Low	2.92	.06	2.80	3.03
Usage	High	1.39	.11	1.16	1.61
	Medium	1.29	.05	1.21	1.38
	Low	1.68	.11	1.46	1.89

5. Discussion

This study aimed to examine potential discrepancies in emotions, attitudes, and social norms toward generative AI, as well as its usage, across different levels of the organizational hierarchy.

Based on identity theory, we proposed and found differences in emotions, attitudes, and perceived social norms toward generative AI across the hierarchy. "Where you sit may determine what you see" holds true in this specific case, as high-level employees experience stronger excitement, less threat, and stronger social norms toward generative AI compared to lower-level employees. This represents, according to literature, a more favorable setting for generative AI usage. Unexpectedly, usage was found to be the highest among low-level employees, with significant difference to middle-level employees. Furthermore, we did not find significant differences in the perceived trustworthiness toward generative AI across the hierarchy, and only significant differences between high-level and middle-level employees for perceived usefulness.

These findings are important because they raise two key questions: First, why is usage among low-level employees the highest, despite their position being associated with more unfavorable conditions in terms of emotions, perceived threat, and social norms? Second, are high-level employees aware of these discrepancies and spending their time on supporting interventions?

5.1 Theoretical Implications

Our study makes the following contributions to literature. We contribute to the literature stream examining predictors of technology usage (Venkatesh & Davis, 2000; Marangunić & Granić, 2015; Blut et al., 2022), specifically AI usage (Rahman et al., 2023; Kelly et al., 2023) and generative AI usage (Ivanov et al., 2024), by adding novel insights into how they vary across corporate hierarchies. The insights for the field of generative AI are consistent with prior extant research indicating differences in emotions, attitudes and perceived social norms between high-level and lower-level employees (Van Kleef & Lange, 2020; Gfrerer et al., 2020; Burks & Krupka, 2012). We further extend this literature stream on variations across hierarchies, by applying identity theory to the domain of generative AI, which has not traditionally been associated with generative AI emotions, attitudes, and perceived social norms. However, it has previously been demonstrated to be suitable in identifying perceptual variances across hierarchical levels within organizations (Treviño et al., 2008). Our findings indicate that distinct identities and roles may lead to diverse emotions and perceived social norms between lower-level employees and higher-level employees, with the latter exhibiting a more positive perspective. Attitudes toward generative AI may only be partially predictable through the role one occupies within an organizational hierarchy.

This highlights the influence of hierarchical positions on generative AI predictors. Furthermore, it emphasizes the need for practical measures to address potential negative effects resulting from these discrepancies. Future research on emotions, attitudes, and perceptions of social norms toward generative AI should consider these distinctions and acknowledge that they can differ between high-level and lower-level employees.

5.2 Practical Implications

Our findings emphasize the importance for high-level employees to actively seek out and understand the emotions, attitudes, and perceptions of lower-level employees, given the significant discrepancies. High-level employees are recommended to foster the exchange with their followers on these factors, with the aim to decrease the risk of disconnected levels and unheard concerns. Thereby, they contribute to the prevention of a potential decline in trust and motivation.

Additionally, high-level employees should actively identify and integrate generative AI use cases into their daily operations to unlock related benefits in their hierarchical levels. This would ensure that their AI excitement and support are seen as authentic and not as pure impression management (He et al., 2023), given their currently low usage rate. Failure to demonstrate authentic AI engagement could negatively impact organizational norms, which significantly influence AI usage (Dye, 2000). On the other hand, one might argue that the low generative AI usage rate (~14%) among high-level employees is inherent to their nature of tasks, meaning that a further integration of use cases may not be feasible. However, managers should ensure that they are already fully leveraging the existing potential of generative AI use cases and remain alert to upcoming opportunities, as technological improvements may offer new possibilities for their daily operations.

Furthermore, high-level employees should target to improve the predictors of generative AI usage among their followers to further increase their usage and unlock additional organizational benefits. In particular, the goal should be to decrease the perceived threat of generative AI and enhance excitement and perceived social norms toward it. Targeted training for lower-level employees should be promoted to educate and inform them about the functions, benefits, and limitations of generative AI.

5.3 Limitations and Suggestions for Future Research

We had the rare opportunity to gather responses from senior managers and compare them to those from middle- and lower-level employees. However, we acknowledge that our study is subject to limitations that present opportunities for future research.

First, our survey respondents are all employed at a multinational software company. The generalizability of the derived results requires therefore a careful consideration. Our data reflects a population with affinity for technology. Hence, we suggest that forthcoming research should collect data from different industries, as well as organization types and scales, to test the hypotheses with a more diverse population and enhance external effectiveness.

Second, future research could delve deeper into the observed contradiction of more favorable emotions (excitement), attitudes (perceived threat), and perceived social norms at the top, yet not exhibiting higher usage rates of generative AI. A potential explanation could be that high-level employees are less involved in operational tasks and therefore encounter fewer use cases for generative AI technologies. To test this explanation, future studies could measure generative AI usage rates in a hypothetical scenario where all hierarchical levels are given the same set of tasks. Alternatively, interviews could be conducted in order to reveal more details on emotions, attitudes, perceived social norms and the observed contradiction regarding generative AI usage. Additionally, the variable usage was in our study based on subjective estimations rather than actual usage data, so we cannot confirm the accuracy of these estimations.

Lastly, given the trend toward flatter organizational structures, one might question the applicability of the findings. However, the gap between top management and lower-level employees persists in many large organizations and is necessary to coordinate tasks and responsibilities. Thus, we contend that these findings likely extend to large organizations and potentially beyond. Future research could explore the hypotheses across different organizational structures.

6. Conclusion

The objective of this paper is to better understand whether and how predictors of generative AI usage, namely emotions, attitudes, and perceived social norms, differ across the corporate hierarchy. Our results reveal that high-level employees tend to exhibit more favorable predictors than lower-level employees, although not leading to higher usage rates yet.

Hence, this study highlights the risk of leaders falling into impression management, given their low usage rates. Furthermore, the findings emphasize the importance of addressing unfavorable variations in these factors among lower-level employees – namely, higher perceived threat, reduced excitement, and weaker perceived social norms toward generative AI. These efforts are crucial in order to increase usage and unlock beneficial organizational results. Lastly, the paper warns about disconnected levels based on discrepancies, which can decline trust and motivation.

7. References

Ajzen, I. (1991). The theory of planned behavior. Organizational behavior and human decision processes, 50(2), 179-211.

Ajzen, I., & Fishbein M. (1977). Attitude-behavior relations: a theoretical analysis and review of empirical research. Psychol Bull, 84, 888-918.

Anderson, C., Hildreth, J. A. D., & Howland, L. (2015). Is the desire for status a fundamental human motive? A review of the empirical literature. Psychological bulletin, 141(3), 574.

Ashforth, B. E., & Mael, F. (1989). Social identity theory and the organization. Academy of Management Review, 14, 20-39.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151, 103745.

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. Journal of managerial psychology, 22(3), 309-328.

Balaskas, S., Panagiotarou, A., & Rigou, M. (2022). The influence of trustworthiness and technology acceptance factors on the usage of e-government services during COVID-19: a case study of post COVID-19 Greece. Administrative Sciences, 12(4), 129.

Bame, A. E., Dugger, W. E. Jr., de Vries, M., & McBee, J. (1993). Pupils' attitudes toward technology–PATT-USA. The Journal of Technology Studies, 19(1), 40-48.

Beaudry, A., & Pinsonneault, A. (2010). The other side of acceptance: Studying the direct and indirect effects of emotions on information technology use. MIS quarterly, 29(3), 689-710.

Bechara, A., Damasio, H., & Damasio, A. R. (2000). Emotion, decision making and the orbitofrontal cortex. Cerebral cortex, 10(3), 295-307.

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. Industrial Management & Data Systems, 119(7), 1411-1430.

Blanca, M. J., Alarcón Postigo, R., Arnau Gras, J., Bono Cabré, R., & Bendayan, R. (2017). Non-normal data: Is ANOVA still a valid option?. Psicothema, 29(4), 552-557.

Blut, M., Chong, A., Tsiga, Z., & Venkatesh, V. (2022). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): challenging its validity and charting a research agenda in the red ocean. Journal of the Association for Information Systems.

Brock, J. K. U., & Von Wangenheim, F. (2019). Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. California Management Review, 61(4), 110-134.

Brockner, J., & Higgins, E. T. (2001). Regulatory focus theory: Implications for the study of emotions at work. Organizational behavior and human decision processes, 86(1), 35-66.

Brynjolfsson, E. L. D., & Raymond, L. R. (2023). Generative AI at Work (No. w31161). National Bureau of Economic Research. doi: 10.3386/w31161

Buchanan, D., Fitzgerald, L., Ketley, D., Gollop, R., Jones, J. L., Lamont, S. S., & Whitby, E. (2005). No going back: A review of the literature on sustaining organizational change. International Journal of Management Reviews, 7(3), 189-205.

Burks, S. V., & Krupka, E. L. (2012). A multimethod approach to identifying norms and normative expectations within a corporate hierarchy: Evidence from the financial services industry. Management Science, 58(1), 203-217.

Cardona, D., Janssen, A., Guhr, N., Breitner, M. H., & Milde, J. (2021). A matter of trust? Examination of chatbot usage in insurance business.

Cerasoli, C. P., Nicklin, J. M., & Ford, M. T. (2014). Intrinsic motivation and extrinsic incentives jointly predict performance: a 40-year meta-analysis. Psychological bulletin, 140(4), 980.

Charness, N., & Boot, W. R. (2009). Aging and information technology use: Potential and barriers. Current directions in psychological science, 18(5), 253-258.

Chui, M., Yee, L., Hall, B., Singla. A., & Sukharevsky, A. (2023). The state of AI in 2023: Generative AI's breakout year. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

Cohen, J. B. (1990). Attitude, affect, and consumer behavior. Affect and social behavior, 152-206.

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. International Journal of Information Management, 60(4), 102383.

Cox, A. M., Pinfield, S., & Rutter, S. (2019). The intelligent library: Thought leaders' views on the likely impact of artificial intelligence on academic libraries. Library Hi Tech, 37(3), 418-435.

Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World: Don't start with moon shots. Harvard Business Review, January-February 2018, 108–116.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use and user acceptance of information technology. MIS Quarterly, 13(3), 319-339.

De Jong, B. A., Dirks, K. T., & Gillespie, N. (2016). Trust and team performance: A meta-analysis of main effects, moderators, and covariates. Journal of Applied Psychology, 101(8), 1134-1150.

Dell'Acqua, F. D., McFowland III, E. M., Rajendran, S. R., Krayer, L. K., Mollick, E. M., Candelon, F. C., Lifshitz-Assaf, H. L., Lakhani, K. R. L., & Kellog, K. C. K. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. Harvard Business School Technology & Operations Mgt. Unit Working Paper.

Dye, R. (2000). The buzz on buzz. Harvard business review, 78(6), 139-146.

Eveslage, C., & Nachtwei, J. (2023). Quo vadis Künstliche Intelligenz in der Arbeitswelt? Perspektiven hochqualifizierter Führungskräfte aus Medizin, Rechtswesen und Politik. In M. Harwardt, P. Niermann, A. M. Schmutte, & A. Steuernagel (Eds), *Lernen im*

Zeitalter der Digitalisierung: Einblicke und Handlungsempfehlungen für die neue Arbeitswelt. Wiesbaden: Springer Fachmedien Wiesbaden.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Reading, Massachusetts: Addison-Wesley.

Gfrerer, A., Hutter, K., Füller, J., & Ströhle, T. (2020). Ready or not: Managers' and employees' different perceptions of digital readiness. California Management Review, 63(2), 23-48.

Gupta, V., & Yang, H. (2024). Generative artificial intelligence (AI) technology adoption model for entrepreneurs: Case of ChatGPT. Internet Reference Services Quarterly, 28(2), 223-242.

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. Academy of management review, 9(2), 193-206.

He, G., Liu, P., Zheng, X., Zheng, L., Hewlin, P. F., & Yuan, L. (2023). Being proactive in the age of AI: exploring the effectiveness of leaders' AI symbolization in stimulating employee job crafting. Management Decision, 61(10), 2896-2919.

Hornsby, J. S., Kuratko, D. F., & Zahra, S. A. (2002). Middle managers' perception of the internal environment for corporate entrepreneurship: assessing a measurement scale. Journal of business Venturing, 17(3), 253-273.

Ivanov, S., Soliman, M., Tuomi, A., Alkathiri, N. A., & Al-Alawi, A. N. (2024). Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour. Technology in Society, 77, 102521.

Janis, I. L., & Mann, L. (1977). *Decision making: A psychological analysis of conflict, choice, and commitment.* Free press.

Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. Telematics and Informatics, 77.

Keltner, D., Gruenfeld, D. H., & Anderson, C. (2003). Power, approach, and inhibition. Psychological review, 110(2), 265.

Kluger, A. N., & Itzchakov, G. (2022). The power of listening at work. Annual Review of Organizational Psychology and Organizational Behavior, 9, 121-146.

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2017). Partnering with AI: how organizations can win over skeptical managers. Strategy & Leadership, 45(1), 37-43.

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with machines: The impact of algorithmic and data-driven management on human workers. Proceedings of the 33rd annual ACM conference on human factors in computing systems, 1603-1612.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. Universal access in the information society, 14, 81-95.

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. International journal of information management, 34(1), 1-13.

Mathieson, K. (1991). Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior. Information systems research, 2(3), 173-191.

Mathieu, J. E., & Zajac, D. M. (1990). A review and meta-analysis of the antecedents, correlates, and consequences of organizational commitment. Psychological Bulletin, 108 (2),171-94.

Mondal, S., Das, S., & Vrana, V. G. (2023). How to Bell the Cat? A Theoretical Review of Generative Artificial Intelligence towards Digital Disruption in All Walks of Life. Technologies, 11(2), 44.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187-192.

Pal, D., Vanijja, V., Thapliyal, H., & Zhang, X. (2023). What affects the usage of artificial conversational agents? An agent personality and love theory perspective. Computers in Human Behavior, 145, 107788.

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of ai on developer productivity: Evidence from github copilot. arXiv preprint arXiv:2302.06590.

Pratt, M. G., & Rafaeli, A. (1997). Organizational dress as a symbol of multilayered social identities. Academy of management Journal, 409, 862-898.

Rahman, M., Ming, T. H., Baigh, T. A., & Sarker, M. (2023). Adoption of artificial intelligence in banking services: an empirical analysis. International Journal of Emerging Markets, 18(10), 4270-4300.

Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., & Spira, M. (2018). Artificial intelligence in business gets real. MIT sloan management review.

Schafheitle, S., Weibel, A., & Rickert, A. (2021). The Bermuda Triangle of Leadership in the AI Era? Emerging Trust Implications From" Two-Leader-Situations" in the Eyes of Employees. Proceedings of the 54th Hawaii International Conference on System Sciences, 5473-5482.

Sherman, G. D., Lee, J. J., Cuddy, A. J., Renshon, J., Oveis, C., Gross, J. J., & Lerner, J. S. (2012). Leadership is associated with lower levels of stress. Proceedings of the National Academy of Sciences, 109(44), 17903-17907.

Stets, J. E. (2004). Emotions in identity theory: The effect of status. In J. H. Turner (Eds), *Theory and research on human emotions* (Vol. 21). Emerald Group Publishing Limited.

Strobel, G., Banh, L., Möller, F., & Schoormann, T. (2024). Exploring generative artificial intelligence: A taxonomy and types.

Stryker, S. (1980). *Symbolic interactionism: A social structural version*. Menlo Park, CA: Benjamin/Cummings.

Stryker, S. (2000). Identity competition: Key to differential social movement participation? In S. Stryker, T. J. Owens, & R. W. White (Eds.), *Self, identity, and social movements.* University of Minnesota Press.

Stryker, S. (2004). Integrating emotion into identity theory. In J. H. Turner (Eds.), *Theory and research on human emotions*. Emerald Group Publishing Limited.

Stryker, S., & Serpe, R. T. (1994). Identity salience and psychological centrality: Equivalent, overlapping or complementary concepts? Social Psychology Quarterly, 57, 16–34.

Treviño, L. K., & Victor, B. (1992). Peer reporting of unethical behavior: A social context perspective. Academy of Management journal, 35(1), 38-64.

Treviño, L. K., Weaver, G. R., & Brown, M. E. (2008). It's lovely at the top: Hierarchical levels, identities, and perceptions of organizational ethics. Business Ethics Quarterly, 18(2), 233-252.

Van Kleef, G. A., & Lange, J. (2020). How hierarchy shapes our emotional lives: Effects of power and status on emotional experience, expression, and responsiveness. Current opinion in psychology, 33, 148-153.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management science, 46(2), 186-204.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. MIS quarterly, 115-139.

Walter, Z., & Lopez, M. S. (2008). Physician acceptance of information technologies: Role of perceived threat to professional autonomy. Decision Support Systems, 46(1), 206-215.

Weaver, G. R., & Agle, B. R. (2002). Religiosity and ethical behavior in organizations: A symbolic interactionist perspective. Academy of Management Review, 27(1), 77-97.

Wilcox, R. R. (2009). Robust ANCOVA using a smoother with bootstrap bagging. British Journal of Mathematical and Statistical Psychology, 62(2), 427-437.

Wood, S.L., & Moreau, C.P. (2006). From fear to loathing? How emotion influences the evaluation and early use of innovations. Journal of Marketing, 70, 44–57.