AI-Driven Informal Learning: The connection between informal learning in the context of human-AI collaboration and workplace collaboration

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Chapter 1 INTRODUCTION

Artificial Intelligence (AI) and, in particular, Large Language Models (LLMs), such as ChatGPT, have quickly become everyday tools in academic and professional settings. Beyond answering general questions, these systems are being used for more complex tasks, such as improving communication tone, supporting programming, facilitating language learning, assisting with research, and solving problems. Their growing presence has sparked interest in their role in self-directed and informal learning. This mode of learning is non-institutional and embedded in daily work processes. It is often triggered by immediate challenges. Informal learning is widely recognized as the most common form of workplace learning and a key driver of skill development, knowledge sharing, and organizational performance.

Recent research suggests that AI tools are reshaping how individuals acquire knowledge and interact within professional environments. While formal education has long benefited from AI applications, workplace adoption has primarily focused on task automation and efficiency gains. However, scholars are increasingly calling for a shift toward AI-assisted informal learning designs that enhance learner autonomy, encourage collaboration, and integrate ethical, human-centered AI practices. The social dimension of AI use is of particular interest. Some studies highlight AI's ability to strengthen collaboration and peer learning, while others caution that AI may inadvertently reduce direct interpersonal engagement.

Despite growing attention, the relationship between AI-driven informal learning and workplace collaboration remains understudied. Specifically, little is known about how the adoption of LLMs interacts with established knowledge-sharing practices or whether these technologies complement or compete with traditional, socially embedded forms of learning. Addressing this gap is essential for organizations seeking to integrate AI tools in ways that preserve the benefits of human collaboration while leveraging the strengths of intelligent systems.

This study investigates the link between AI use, informal learning, and workplace collaboration. The research question guiding this study is: How is AI-driven informal learning linked to workplace collaboration and knowledge sharing? Drawing on interdisciplinary literature and empirical survey data, the study examines the frequency and purposes of LLM use, perceptions of usefulness and ease of use, and the interplay between AI literacy, informal learning behaviors, and social knowledge-sharing activities. The study aims to contribute theoretical insights into human–AI collaboration in informal learning environments and practical recommendations for the productive and balanced integration of AI into organizational learning cultures.

RQs: "How is AI-driven informal learning linked to workplace collaboration and knowledge sharing?"

Chapter 2 RELATED WORK

Artificial intelligence in learning contexts spans several interconnected research domains. Rienties et al. (2020) identify four primary areas: Artificial Intelligence in Education (AIED), Computer-Supported Collaborative Learning (CSCL), Educational Data Mining (EDM), and Learning Analytics (LA). AIED focuses on simulating and predicting learning processes using AI techniques, while CSCL emphasizes the social and collaborative dimensions of technology-mediated learning. EDM and LA both adopt data-driven approaches to understanding and improving learning processes. EDM typically identifies patterns in educational data, while LA takes a more holistic, system-level view. Rienties et al. (2020) argue that, despite often being siloed, these fields should collaborate more closely to address complex educational challenges.

This interdisciplinary perspective is directly relevant to the present study, which lies at the intersection of AIED and CSCL and incorporates elements of LA in its survey-based exploration of AI-driven informal learning and workplace collaboration. The study draws on theoretical and empirical insights from these domains to examine how AI tools, particularly large language models (LLMs), affect the social and collaborative aspects of informal learning.

2.1 Informal Learning: Definitions and Theoretical Perspectives

Informal learning is widely recognized as the most prevalent form of work-related learning, characterized by being non-institutionally organized, integrated into daily work processes, and often triggered by work-related challenges (Decius, 2024). Three theoretical perspectives dominate research on informal learning (Decius, 2024):

1. **Dimensional approaches** distinguish informal learning from other learning types on continua, treating dimensions as spectra rather than discrete categories.
2. **Learning-source-based approaches** classify learning by information sources such as the self, peers, or non-interpersonal channels.
3. **Process-oriented approaches** view learning as cyclical, as exemplified by Tannenbaum et al.'s dynamic model.

De Grip et al. (2024) highlight that "learning by doing" and "learning from peers or supervisors" are more effective for human capital development than formal training. Knowledge spillovers among co-workers substantially enhance firm productivity, with informal learning activities accounting for 91% of learning-related time in the Netherlands. While valuable for all age groups, informal learning has a particularly strong impact on younger workers' performance. Human resource practices—such as coaching, regular feedback, and "new ways of working" (e.g., flexible schedules, output-based management, and knowledge accessibility)—play a critical role in fostering informal learning. A notable drawback, however, is that skills acquired informally are less visible to external employers, potentially reducing their labor market value.

Tannenbaum et al. (2024) refine the concept with Informal Field-Based Learning (IFBL), defined as intentional, self-directed behavior aimed at acquiring work-relevant, organizationally valued knowledge outside formal programs. IFBL, which accounts for 70–90% or more of workplace competency acquisition, comprises three subdimensions: (1) feedback-seeking and reflection-based learning, (2) vicarious learning, and (3) learning through experimentation and new experiences. To organize existing knowledge and identify enabling factors, the authors propose the CAM-OS framework, consisting of Capability, Awareness, Motivation, and Opportunity, with Support as an overarching element.

2.2 AI in Workplace and Informal Learning Contexts

The impact of AI on informal learning remains an emerging field of study (Holmes et al., 2024). While AI in formal education has been investigated for over four decades, workplace applications have so far centered on automating tasks, improving efficiency, matching employees with training, and providing faster information access—rather than being seamlessly embedded within work activities. Holmes et al. advocate for a paradigm shift towards AI-assisted informal learning designs that enhance learner agency, support social and mutual learning, foster self-regulation, respect human rights, and integrate ethical-by-design AI techniques alongside innovative pedagogies.

Przegalinska et al. (2025) demonstrate that integrating AI significantly improves performance across task types, most notably in routine tasks and decision-support, but also in creative and innovative processes, regardless of complexity. Similarly, Callari et al. (2025) position AI as complementary to human work, with its benefits highly dependent on workplace culture and integration strategies. Karhapää et al. (2023) note that AI can either foster social interactions when supporting knowledge sharing or hinder them when used to automate communication.

2.3 Social Dimensions of AI Use in Learning

Rafi et al. (2024) find that perceived usefulness and trust in AI tools such as ChatGPT strongly affect adoption, which in turn positively impacts employee performance. However, Hohenstein et al. (2021) caution that AI-generated responses, such as algorithmically phrased emails, can alter perceptions of engagement and authenticity. Their experiments reveal that while smart replies increase efficiency and positivity in communication, they may also influence both pro-social and anti-social behaviors.

Sahni et al. (2025) report that employees prefer experiential and social learning methods, along with external tools like ChatGPT, over company-provided training materials. Seven out of ten participants in their study tended to disregard formal training in favor of peer-driven learning environments, highlighting the need for organizations to strengthen informal and socially embedded learning opportunities.

2.4 AI for Self-Directed and Digital Informal Learning

Li et al. (2024) examine how YouTubers utilize ChatGPT for self-directed language learning (SDLL), proposing an AI-integrated SDL framework that builds upon Song and Hill's model, a model of self-directed learning in online environments, integrating learner attributes, learning processes, and contextual factors. Effective use of ChatGPT involves strategic prompting, critical evaluation of responses, and iterative dialogue. They acknowledge, however, that their reliance on self-reported data is a limitation, recommending future longitudinal or observational studies.

Rehman et al. (2024) investigate the role of AI competence in digital informal learning, finding that it boosts engagement, chatbot use, and perceived autonomy. Both digital informal learning and chatbot use positively influence student engagement, with chatbots particularly enhancing autonomy. They caution that their study's focus on Saudi university students limits generalizability, suggesting future research include cultural comparisons and additional mediating factors such as self-efficacy and technology access.

2.5 AI, Knowledge Sharing and Organizational Learning

Talet (2024) identifies three main ways AI facilitates knowledge sharing: as a mediator, facilitator, or active participant. Through automation, recommendation, and personalization, AI can store and retrieve information, filter and suggest relevant knowledge, foster human–human or human–machine interactions, and collaborate in creating new knowledge. Challenges include capturing tacit knowledge, maintaining trust and privacy, balancing automation with human agency, and preventing over-reliance on AI outputs.

Shaikh et al. (2023) show that AI enhances productivity both directly and indirectly via knowledge sharing, with employee mental health and well-being (EMHWB) also influencing productivity. However, EMHWB does not mediate the AI–productivity link.

Jarrahi et al. (2024) advocate for a collaborative intelligence model, wherein AI augments rather than replaces human judgment. For effective AI integration in knowledge management, organizations must align three dimensions: people (enhancing capabilities and critical engagement), infrastructure (ensuring high-quality, transparent, and accessible data), and processes (maintaining human oversight, aligning AI outputs with domain expertise, and freeing capacity for strategic work).

2.6 AI in Collaborative and Technology-Supported Informal Learning

Tan et al. (2022) systematically review AI applications in collaborative learning over two decades, finding that most studies (51.2%) focus on prescriptive interventions such as optimal group assignments or feedback provision. Intelligent agents, capable of perceiving, reasoning, and acting, are particularly effective in analyzing learner behavior and enhancing complex collaborative tasks.

Tavakoli et al. (2022) propose a hybrid human–AI curriculum development framework for personalized informal learning, integrating AI with crowdsourcing to define and update learning goals, skills, topics, and content. Quality is ensured through voting and point systems that reward reliable contributors. Expert interviews with senior professionals validate the system's potential for dynamic curriculum creation.

Zheng et al. (2019) review 70 studies on technology-supported collaborative learning in informal settings, using an adapted activity theory framework to analyze six key elements: subjects, objects, rules, contexts, interactions, and tools. They emphasize growing scholarly interest in this domain and provide a structured foundation for future research and design.

Chapter 3 METHODS

This study adopts an approach of creating a questionnaire aligned with related work to further validate findings from existing research. The related work focuses on the current state of knowledge regarding informal learning and the impact of AI on the social aspects of self-directed learning. The questionnaire includes common items found in literature investigating AI literacy, AI usage at work, the perceived impact on informal learning and social interactions, knowledge sharing with colleagues, and adoption and attitude perception. Most questionnaires are quantitative in nature, using a Likert scale for responses.

No specific participant group is defined. The target is to collect at least 60 completed responses. The survey will be published and managed via the LimeSurvey tool. Analysis of the collected responses will be conducted using Python (for correlation analysis and token-based text processing) and Microsoft Excel (pivot tables) to identify patterns and relationships within the data.

Chapter 4 EXPECTED OUTCOMES

This study aims to provide a deeper understanding of the impact of AI on informal learning. Ideally, the findings will allow for the derivation of recommendations for educational institutions and employers on how to facilitate AI adoption for students and employees, in alignment with current literature. The study also seeks to identify correlations between AI attitude/adoption, usage patterns, and perceived benefits.

From a theoretical perspective, this study intends to contribute to the ongoing discussion on human–AI collaboration in informal learning environments by offering empirical insights. From a practical perspective, it aims to provide strategies that balance AI-driven automation with human interaction in learning environments. These strategies will be informed by best practices identified in the literature and the empirical results of the study.

Chapter 5 Survey

For the survey, a questionnaire was built to address the above-mentioned questions. The main part is quantitative, followed by a qualitative section in the end. It is a mix of own questions, questions derived from questionnaires found in literature and questions developed by a research associate at the University of Hamburg. The full questionnaire with the specific questions can be found in the appendix.

Measuring constructs

Construct	**Source**
Quantitative Part	
Demographics	own
Responsibility	
LLM Literacy	MAILS – Meta AI literacy scale
Frequency of use	own
LLM Task Complexity	Task Complexity (Stock, 2006)
Colleague Task Complexity	
Informal Learning (Non-LLM)	study group of R. Kirmse; based on Decius et al. (2019)
Informal Learning (LLM)	
Written Contribution	KSBS – Knowledge Sharing Behavior Scale
Organizational Communication	
Community Contribution	
Perceived Ease of Use	TAM – Technology Acceptance Model
Perceived Usefulness	
Qualitative Part	
Personal Use cases of LLMs such as ChatGPT	“AI and science: what 1,600 researchers think” – nature, 2023
Most impressive, useful example of AI tools	
Most concerning example of AI tools	

Table 1: Constructs with their respective source

As with most surveys, the demographics of the participants were captured to better understand if there are differences in usage patterns based on age, gender, work experience, and workplace hierarchy. The Responsibility construct was added to provide a further validating measure of whether the participant performs more “low-level” or “high-impact” work with regard to colleagues and the organization.

To better understand how familiar or competent participants perceive their ability to use LLMs, a subset of the MAILS questionnaire by Carolus et al. (2023) was used. The first 15 question items (QIs), which measure the ability to apply, understand, and detect AI, were used.

To better understand LLM usage, two distinct questions were included: one quantitative and one qualitative. The quantitative question simply asks participants how often they use LLMs, while the qualitative question, taken from a 2023 Nature magazine report titled "AI and Science: What 1,600 Researchers Think," asks participants to describe the most common uses of LLMs.

LLM and colleague task complexity constructs were taken from Stock (2006) to better understand the relationship between demographics, AI literacy, and task complexity.

Informal learning constructs were divided into informal learning with and without an LLM. These questions were developed by a study group led by Kirmse at the University of Hamburg and are based on Decius et al. (2019). The questions cover topics such as model learning, direct feedback, and intrinsic/extrinsic intent to learn.

As stated by De Grip et al. (2024), knowledge sharing is an important social aspect of informal learning. This makes studying and better understanding its relation to participants important. To do so, the Knowledge Sharing Behavior Scale (KSBS) by Ji (2009) is used. The KSBS captures three dimensions: written contributions, which entails communicating via the sharing of documentation from personal files and sharing ideas and thoughts with internal company databases; organizational contributions, which focus on exchanging information during work-related meetings and interpersonal communication; and community contributions, which capture sharing knowledge with members of the same field or industry who are not part of the organization.

For the quantitative part, the Technology Acceptance Model by Davis (1989) is used to better understand the participants perceived ease of use and usefulness of LLMs.

For the qualitative portion, two questions from the Nature article are used: the first asks about the most impressive example of AI, and the second asks about the most concerning example of AI.

Chapter 6 Analysis

Pre-requisites / Preprocessing

A core part of the analysis will involve constructing a correlation matrix over the measured constructs. Prior to analysis, data cleaning is essential. Out of the 53 participants who engaged with the survey, 34 completed it. Only the responses of those who completed the survey will be considered. Additionally, participants who provided implausible demographic data will be excluded from the analysis. For instance, one participant will be omitted as they entered their age as 199, rendering all other entries for this individual questionable.

Participants
Of the 33 participant 18 (54.55%) identify as male and 15 (45.45%) as female. The mean age is 31.85 with a standard deviation of 11.03. The majority of participants reported to study and/or work in the field of Information Technology (39.39%), followed by Finance/Banking and Engineering/Tech Industry (12.12% respectively). Of all participants 15 reported *employee* as main occupation and another 15 *student.*

Testing load factor of q items to construct
To test the reliability of the underlying individual question items measuring overlaying construct, the Cronbach's-alpha test was done with the results provided in the following table:

Construct	**Q-Items Code**	**Cronbach's-Alpha**
Responsibility	DemQ51[SQ001-SQ006]	0.862
LLM Literacy	LitQ01[SQ001- SQ015]	0.933
LLM Task Complexity	GTCQ01[SQ001- SQ005]	0.576
Colleague Task Complexity	GTCQ02[SQ001- SQ005]	0.771
Informal Learning (Non-LLM)	ILQ01[SQ002_3_4_7]	0.880
Informal Learning (LLM)	ILQ01[SQ001-SQ015]–NO_LLM	0.828
Written Contribution	WrittQ01[SQ001_2]	0.604
Organizational Communication	OrgQ01[SQ001-SQ008]	0.801
Community Contribution	CommQ01[SQ001-SQ007]	0.916
Perceived Ease of Use	PEUQ01[SQ001-SQ006]	0.902
Perceived Usefulness	PUQ01[SQ001-SQ007]	0.960

Table 2: Constructs, the respective Qitems and the measured Cronbach's-Alpha

All constructs achieved a cronbach's alpha value higher than 0.7 except constructs "LLM Task Complexity" and "Written Contribution"**.** The implication of that will be further discussed in section "Discussion".

Chapter 7 Results

This section will cover the quantitative and qualitative part of the survey.

Quantitative Part

Frequency of LLMs use

As indicated by the works of Rafi et al. (2024), Hohenstein et al. (2021), Jarrahi et al. (2024), Przegalinska et al. (2025), and Talet (2024), the integration of AI has become a pervasive phenomenon. Therefore, it is essential to understand the frequency of use exhibited by the participants. As illustrated in the accompanying graph, the majority of participants (13 out of 33; 39.39%) report using LLMs multiple times per week, with 24.24% reporting daily use. This finding aligns with the extant literature on the widespread adoption of these models.

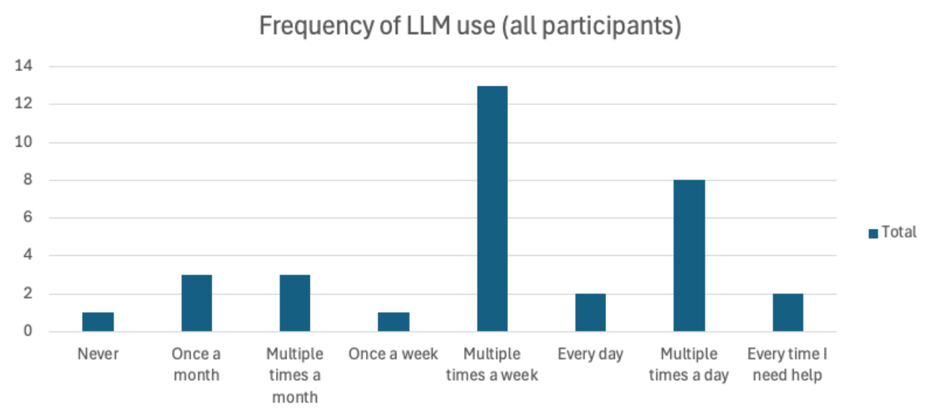

Figure 1: Frequency of LLM use of all participants

Significant Correlations

With total participants n = 33 we get a degree of freedom (df) value of df = n – 2 = 31. With reference to the t-table provided by the University of Washington [21], with a two-sided alpha of 0.05 and a df value of 30 (closest value found in table to real df), we get a t value of 2.04.

$$r_{\text{critical}} = \sqrt{\frac{t^2}{t^2 + \text{df}}}$$

Using above formular, this results into $r_{critical}$ of 0.344.

Correlations to highlight

The below table highlights notable correlations that were deemed interesting. The full table of correlations can be found in the appendix.

Variable 1	**Variable 2**	**Correlation**
AI Literacy	Frequency of Use	0.712
Frequency of Use	Informal Learning LLM	0.624
Frequency of Use	Perceived Usefulness	0.618

AI Literacy	Informal Learning LLM	0.615
IL NON LLM	Organizational Comms	0.524
Frequency of Use	Perceived Ease of Use	0.502
IL NON LLM	Community Contributions	0.391
Responsibility	IL NON LLM	0.361
Time In Position	AI Literacy	-0.353
Age	AI Literacy	-0.355
Time in Position	Frequency of Use	-0.363
Years work experience	Frequency of Use	-0.369
Years work experience	AI Literacy	-0.378
Hierarchy	AI Literacy	-0.387
Hierarchy	Frequency of Use	-0.448

Table 3: Notable correlations of respective constructs

The strongest notable correlation, 0.712, is observed between AI Literacy and the frequency of using a Large Language Model (LLM). This aligns with expectations, as higher usage is likely associated with greater AI Literacy. Additionally, there is a strong correlation of 0.624 between frequency of use and the construct "Informal Learning LLM," indicating that participants who frequently utilize LLMs also integrate them into their informal learning processes. Similarly, participants with higher scores in AI Literacy tend to exhibit higher scores in informal learning involving LLMs. This is in line with Rehman et al. (2024) who found that AI competency significantly enhances engagement in digital informal learning and chatbot use.

Outside the direct realm of LLMs, the data reveals that the degree of informal learning without LLMs demonstrates a moderate positive correlation with Organizational Communication (0.524) and Community Contributions (0.391). This is in line with findings of De Grip et al. (2024) emphasizing that learning from peers or supervisors and knowledge spillovers among co-workers are critical drivers of development and additionally aligns with the work of Karhapää et al. (2023) who identified digital work practices like sharing knowledge and relational communication as promoters of informal workplace learning. Interesting to highlight is, that participants with higher responsibility in their job, also moderately positively correlate (0.361) with informal learning not involving LLMs.

The findings of Rafi et al (2024) that perceived usefulness correlates with adoption is found here with a moderate to strong correlation (0.618). Additionally, one can find the other dimension of the TAM, where perceived ease of use is moderately positively correlated with frequency of use (0.502).

Interestingly, several moderate negative correlations have been observed. Frequency of use negatively correlates with time in position (-0.363), years of work experience (-0.369), and hierarchy (-0.448). This suggests that individuals with more work experience or higher hierarchical positions tend to engage less frequently with LLMs. Moreover, AI Literacy also negatively correlates with time in position, age, years of work experience and hierarchy, further reinforcing the trend that literacy and frequency of use exhibit strong correlations. This suggests that younger or less senior employees are more frequent users and have higher AI literacy. This complements the findings of Sahni et al. (2025) who noted a preference for external tools like ChatGPT over traditional company training, a behavior that may be more common among a younger demographic.

Qualitative Part

Additionally, to the quantitative part, the questionnaire had three qualitative questions regarding participants use cases of LLMs, impressive/useful examples and also perceived concerning cases that participants perceived. The answers were tokenized in the analysis to better understand which terms are used most.

Global token cloud **personal use cases of LLMs**

The word/token cloud for personal use cases indicate that idea and text creation are the two most common cases when using LLM followed by supportive and translation tasks.

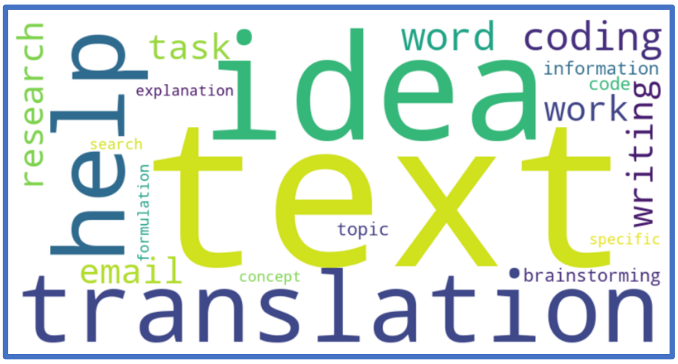

Figure 2:

Token summary with examples for **personal use cases of LLMs**

Term	Occurrences of individual responses with term	Example response
idea	4	"translations, formulations, explanations, **conceptualization of <u>ideas</u>"; "**Improve writing, translation, **gather <u>ideas</u>, learn** about new topics/concepts do work, privately for recipes and medicines"
translation	4	"Text **creation, <u>translation</u>, clarification** of a task…"; "Mainly **for <u>translation</u> purposes** and feedback on my ideas, as well as movie references when I have a solid story idea"
coding	4	**"<u>Coding</u> assistance"; "<u>Coding</u>**, Q&A"

email	3	**“Writing Emails**, concepts for work. Help with coding.**”; “For E-mails**, explaining some definitions, to find a specific concept**”**
help	3	**“**Literature search, generating summaries, improving language for written text, **help with programming”**
writing	3	**“Writing scientific papers**, finding sources, correcting grammar and style, suggesting books, movies and music**”**
work	3	**“**Writing emails, **concepts for work**. Help with coding.**”**

Table 4: token occurrences for personal LLM use

Participants identified the most common personal use cases as tasks related to creating ideas and text, such as generating concepts, drafting written content (e.g., emails or scientific papers), and performing translations. These findings align with those of Li et al. (2024), who emphasize that effective AI-supported self-directed learning frequently requires iterative prompting and refinement of written outputs. Beyond language-related tasks, LLMs were frequently used for technical assistance, especially for coding support and general help with work-related problem solving. This reflects Przegalinska et al.'s (2025) observation that AI integration can improve performance in routine and complex tasks. The diversity of reported applications suggests that LLMs are not limited to narrow, domain-specific uses, but instead function as flexible cognitive tools capable of supporting a broad spectrum of informal learning activities. This versatility positions LLMs as embedded digital collaborators within daily workflows, consistent with Holmes et al.'s (2024) call for AI tools that are seamlessly integrated into professional practice to foster autonomy, adaptability, and collaborative knowledge building.

Global token cloud for **impressive/useful examples of LLMs**

Figure 3: Global token cloud for impressive/useful examples of LLMs

Token summary with examples for **impressive/useful examples of LLMs**

Term	**Occurrences of**	**Example response**

	individual responses with term	
idea	5	"When I'm new to a project I like to **use LLMs to <u>get a first idea</u> of important** aspects that need to be considered.**"; "<u>Idea generation</u> on how to solve a problem** or to create a certain strategy for a goal**"**
solve	5	"Sometimes AI is more empathetic than doctors (**Chat GPT <u>always tries to solve problems</u>** and listens closely)**"; "<u>Solve repetitive</u> homework tasks**. Write general essays, etc...**"**
research	3	"ChatGPT is very impressive. For instance, when thinking about a **<u>research design</u> it can really help organizing** your ideas and coming to a clear proposal.**"; "Collect <u>research</u> data**"
information	3	"The way it **helps to search for and compile <u>information</u>** that would take me a long time to do by myself"; "Summarizing, write communication in different styles e.g as post, **stakeholder <u>information</u>**, management update"
work	3	"**Softening the initial learning curve** when having to **<u>work</u>** with **unfamiliar** (but overall well-established) **technologies** and **programming languages**."; "In my student life, summarizing papers and refining style. In my work as a sound engineer, AI sample creation tools."
task	3	"**Solve repetitive <u>tasks</u>** with long lists fast and reliable"

Table 5: token occurrences impressive/useful examples of LLMs

When asked about the most impressive or useful applications, participants consistently mentioned LLMs' ability to solve complex problems and simplify research processes by quickly organizing and summarizing large amounts of information. These tools were valued beyond simple retrieval for enabling deeper exploration of unfamiliar topics. They often serve as cognitive scaffolds that accelerate comprehension, an effect also noted by Przegalinska et al. (2025). They emphasize AI's capacity to enhance routine and creative tasks. Idea generation was identified as a particularly valuable function, supporting activities such as brainstorming strategic approaches, generating alternative solutions, and framing new perspectives on a problem. This creative support extends beyond abstract thinking to concrete work scenarios, such as drafting project outlines and devising problem-solving pathways. This aligns with Li et al.'s (2024) findings on AI-facilitated self-directed learning. One participant remarked that AI can "soften the initial learning curve" when working with unfamiliar technologies, reflecting LLMs' role as adaptive learning companions in informal, self-directed contexts. In this sense, LLMs appear to bridge the gap between initial exposure and functional competence. They reduce entry barriers and enable users to integrate new knowledge more quickly into their professional and academic practices. This is consistent with Holmes et al.'s (2024) call for AI-assisted learning designs that enhance learner agency and self-regulation.

Global token cloud for **concerning examples of LLMs**

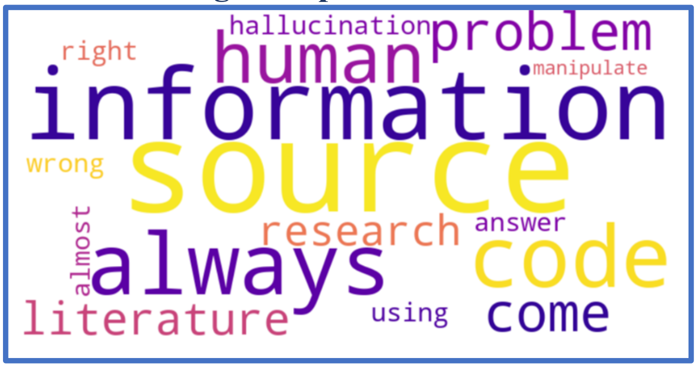

Figure 4: Global token cloud for concerning examples of LLMs

Token summary with examples for **concerning examples of LLMs**

Term	**Occurrences of individual responses with term**	**Example response**
source	4	"ChatGPT is very unhelpful when it comes to literature research. Sometimes it just **invents sources** or has problems finding credible papers regarding a topic."; **"People not verifying whether the answer actually comes from the sources** in critical tasks."
information	4	"The **information is not always what I'm looking for**, so I have to verify or cross-check what it shows"; "AI **making up information** when creativity level in the parameter settings is set to high"
code	3	**"Low-quality "AI slop" code** and documentation"
used	3	"Trusting LLMs too much. I've seen colleagues using technical values calculated by LLMs which where magnitudes off the actual value because **wrong engineering equations where being used** or the right equations were used incorrectly or with false assumptions."; **"you get used to it** and the next time you just immediately rely on LLMs."
literature	2	**"Uncritical use for literature** search and hallucination of sources"

Table 6: token occurrences for concerning examples of LLMs

The concerns voiced by participants closely mirror the issues raised in existing literature on AI adoption. Several respondents cited instances of LLMs "hallucinating" sources or providing inaccurate information, especially in contexts like literature searches or technical problem solving. This aligns with Li et al.'s (2024) emphasis on the critical need to rigorously evaluate AI outputs to mitigate the risk of fabricated or misleading content. Similarly, Farrokhnia et al. (2024) highlight the importance of cultivating digital literacy and critical thinking skills to enable users to identify and correct such inaccuracies. Beyond factual reliability, participants expressed apprehension about overreliance on AI. They warned that habitual dependence could erode independent problem-solving skills, an observation consistent with the framework of Jarrahi et al. (2024), which advocates for maintaining human oversight and encouraging active, critical engagement with AI-generated outputs to counter potential biases and safeguard accuracy. Concerns about the erosion of authenticity in communication resonate with Hohenstein et al.'s (2021) findings. They caution that, while efficient, AI-mediated interactions may subtly alter perceptions of sincerity and interpersonal connection. Together, these concerns emphasize that, although LLMs offer powerful capabilities, their effective and ethical use depends on sustained human judgment, transparent verification practices, and an organizational culture that prioritizes innovation and critical discernment.

Chapter 8 Discussion

The findings of this study provide empirical evidence of the interplay between large language model (LLM) use and informal learning *with* LLMs. Consistent with prior studies (Rehman et al. (2024), Li et al. (2024)), the results indicate that higher AI literacy is significantly linked to increased LLM usage frequency and the integration of LLMs into informal learning processes. These results reinforce the idea that proficiency in AI tools encourages adoption and facilitates deeper incorporation into daily, self-directed learning practices. The strong correlation between AI literacy and usage frequency ($r = 0.712$) aligns with technology adoption theories, particularly the Technology Acceptance Model (Davis, 1989), which states that perceived usefulness and ease of use encourage engagement. In this study, both constructs were positively correlated with the frequency of use, indicating that users who find LLMs intuitive and beneficial are more likely to incorporate them into their workflows. These results suggest that targeted AI literacy training could further increase adoption, particularly among employees who are less inclined to experiment with emerging technologies.

The study also revealed a significant generational and hierarchical divide in AI engagement. Negative correlations between usage frequency and factors such as years of work experience, hierarchy level, and time in position suggest that younger or less senior individuals tend to be the most frequent LLM users. This finding aligns with that of Sahni et al. (2025), who reported that younger employees are more likely to bypass formal training in favor of self-directed, technology-enabled learning. From an organizational perspective, this highlights a potential gap in AI adoption among senior staff, which could hinder knowledge sharing and cross-generational collaboration. Bridging this gap will likely require interventions that emphasize the strategic value of AI beyond task automation. The positive association between informal learning without LLMs and organizational communication ($r = 0.524$) and community contributions ($r = 0.391$) emphasizes that traditional peer-based learning is a critical driver of workplace knowledge exchange (De Grip et al. (2024)). Interestingly, participants with higher responsibility scores also engaged more in non-LLM informal learning. This suggests that leadership roles may rely heavily on interpersonal learning modes rather than AI-mediated ones. This suggests that, despite growing adoption, LLMs currently play a negligible role in the relational dynamics that continue to define many professional settings.

Nevertheless, the survey data indicate that LLM use was accompanied by an overall rise in informal learning activity, yet no significant positive or negative correlations emerged between LLM use and the Knowledge Sharing Behavior Scale. This finding complicates the ability to conclusively answer the research question (How is AI-driven informal learning *linked* to workplace collaboration and knowledge sharing?) and underscores the need for further investigation. Equally noteworthy is that no significant associations were observed between gender and any of the constructs, suggesting that this demographic factor has a negligible influence within this context. Taken together, these quantitative results highlight both the potential and the current limitations of AI-driven learning as a catalyst for organizational knowledge flows.

Building on these observations, the qualitative findings further illustrate how participants personally engage with LLMs. Reported use cases such as idea generation, translation, text drafting, and coding assistance underscore their versatility and alignment with the problem-driven nature of informal learning. Similarly, "impressive" use cases often involved accelerating research or reducing onboarding time for unfamiliar technologies, which reinforces the literature's view of AI as a tool that lowers barriers to entry in new domains (Przegalinska et al. (2025)). However, concerns about hallucinated sources, inaccurate outputs, and overreliance on AI align with Li et al.'s (2024) emphasis on critical evaluation skills and Jahrrahi et al.'s (2024) call for maintaining human oversight. From a practical standpoint, these results suggest that organizations aiming to leverage AI for learning should adopt a dual strategy of promoting AI literacy to enable the meaningful use of LLMs while safeguarding and enhancing traditional social learning channels. Rather than treating AI as a solitary productivity tool, integrating it into collaborative learning frameworks may foster more sustainable knowledge sharing and mitigate the risks of isolation or over-automation.

Nevertheless, the study has clear limitations. The smaller-than-intended sample size ($n = 33$) restricts statistical generalizability, and the reliance on self-reported data introduces potential biases related to accuracy and impression management by participants. Additionally, while most constructs achieved satisfactory internal consistency (Cronbach's $\alpha > 0.7$), "LLM Task Complexity" and "Written Contribution" fell slightly below this threshold. This indicates that these constructs may need to be refined in future research to ensure they more reliably capture the intended dimensions of LLM use and output quality. As with similar studies (Li et al. (2024), Rehman et al. (2024)), future research would benefit from mixed methods designs, including observational or longitudinal approaches, to capture how LLM use, and informal learning practices evolve over time. Additionally, investigating sector-specific dynamics and cultural factors could refine our understanding of adoption barriers and enablers.

Overall, this research contributes to the growing body of literature on AI-driven informal learning by showing that LLM adoption is closely linked to individual competencies and workplace social structures. While AI tools are powerful enablers of self-directed learning, integrating them optimally into collaborative environments will require strategies that combine technological proficiency with human-centered learning practices.

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APPENDIX

Questionnaire as found in survey

1. Demographic Information		
Item	**Question code**	**Question**
Item 1	DemQ01	What is your gender?
Item 2	DemQ02	What is your age?
Item 3	DemQ03	What is your current main occupation?
Item 4	DemQ04	Which field or industry do you primarily work or study in?

Item 5	DemQ07	Do you work/study full-time or part-time?
Item 6	G01Q31	How many years of total work experience do you have in your current field or industry?
Item 7	DemQ055[SQ001][SQ002]	How long have you been in your current role/position?
Item 8	DemQ05	What is your position or hierarchy level within your academic field or industry?
Item 9	DemQ06	What is the typical size of the team you work in?
1.1 Level of Responsibility		
Item 1	DemQ51[SQ001]	Making significant decisions that affect my team/department/organization.
Item 2	DemQ51[SQ002]	Managing budgets or having financial oversight.
Item 3	DemQ51[SQ003]	Supervising or leading other employees.
Item 4	DemQ51[SQ004]	Responsibility for key projects or deliverables.
Item 5	DemQ51[SQ005]	Autonomy in how I carry out my work.
Item 6	DemQ51[SQ006]	Accountability for meeting specific targets or outcomes.

2. **AI Literacy** (MAILS – Meta AI literacy scale (https://doi.org/10.1016/j.chbah.2023.100014))		
Item	**Question code**	**Question**
Item 1	LitQ01[SQ001]	I can operate LLM applications in everyday life.
Item 2	LitQ01[SQ002]	I can use LLM applications to make my everyday life easier.
Item 3	LitQ01[SQ003]	I can use LLMs meaningfully to achieve my everyday goals.
Item 4	LitQ01[SQ004]	In everyday life, I can interact with LLMs in a way that makes my tasks easier.
Item 5	LitQ01[SQ005]	In everyday life, I can work together gainfully with an LLM.
Item 6	LitQ01[SQ006]	I can communicate gainfully with LLMs in everyday life.
Item 7	LitQ01[SQ007]	I know the most important concepts of the topic “artificial intelligence”.
Item 8	LitQ01[SQ008]	I know definitions of artificial intelligence.
Item 9	LitQ01[SQ009]	I can assess what the limitations and opportunities of using an LLM are.

Item 10	LitQ01[SQ0010]	I can assess what advantages and disadvantages the use of an LLM entails.
Item 11	LitQ01[SQ0011]	I can think of new uses for LLMs.
Item 12	LitQ01[SQ0012]	I can imagine possible future uses of LLMs.
Item 13	LitQ01[SQ0013]	I can tell if I am dealing with an application based on LLMs.
Item 14	LitQ01[SQ0014]	I can distinguish devices that use LLMs from devices that do not.
Item 15	LitQ01[SQ0015]	I can distinguish if I interact with an LLM or a real human.

3. AI Usage in the Workplace (Qs from "AI and science: what 1,600 researchers think" – nature, 2023		
Item	**Question code**	**Question**
Item 1	UseQ01[SQ001]	How often do you use generative AI tools (such as ChatGPT) at work?
Item 2	UseQ02	What do you use generative AI tools (such as ChatGPT and other large language models) for?

4. Task Complexity		
LLM Task Complexity		
Item	**Question code**	**Question**
Item 1	GTCQ01[SQ001]	The tasks I solve using LLMs include much variety. include much variety.
Item 2	GTCQ01[SQ002]	The tasks I solve using LLMs mainly consist of solving complex problems.
Item 3	GTCQ01[SQ003]	The tasks I solve using LLMs hardly consist of routine work.
Item 4	GTCQ01[SQ004]	The tasks I solve using LLMs require the assessment of a large amount of information/alternatives.
Item 5	GTCQ01[SQ005]	The tasks I solve using LLMs consist of numerous different elements.
Colleague Task Complexity		
Item 1	GTCQ02[SQ001]	The tasks I solve with colleagues include much variety.
Item 2	GTCQ02[SQ001]	The tasks I solve with colleagues mainly consist of solving complex problems.
Item 3	GTCQ02[SQ001]	The tasks I solve with colleagues hardly consist of routine work.
Item 4	GTCQ02[SQ001]	The tasks I solve with colleagues require the assessment of a large amount of information/alternatives.

Item 5	GTCQ02[SQ001]	The tasks I solve with colleagues consist of numerous different elements.

5. Informal Learning (study group of R. Kirmse; based on Decius et al. (2019))		
Item	**Question code**	**Question**
Item 1	ILQ01[SQ001]	I use my own ideas to solve tasks.
Item 2	ILQ01[SQ002]	I closely inspect how LLMs solve tasks to improve my own solutions.
Item 3	ILQ01[SQ003]	I consult LLMs when I am not sure about how well I solved a task myself.
Item 4	ILQ01[SQ004]	I consult LLMs about which methods and tricks can be used for solving tasks.
Item 5	ILQ01[SQ005]	Before starting with a new task, I think about how to solve it in the best way possible.
Item 6	ILQ01[SQ006]	After finishing a task, I think about how to solve the next one more efficiently and more precisely.
Item 7	ILQ01[SQ007]	While solving a task, I want to learn something from LLMs, so that I can use that knowledge to solve the following task better.
Item 8	ILQ01[SQ008]	I want to learn something for myself, because I can then solve the following tasks faster.
Item 9	ILQ01[SQ009]	I look at how others work in the company to improve my work.
Item 10	ILQ01[SQ0010]	I ask my colleagues when I am not sure how well I worked.
Item 11	ILQ01[SQ0011]	I ask my colleagues about the methods and tricks they use at work.
Item 12	ILQ01[SQ0012]	Before starting a new task, I think about how I can do my work best.
Item 13	ILQ01[SQ0013]	When I have finished a new task, I think about what I still could do better next time.
Item 14	ILQ01[SQ0014]	I want to learn something new at work for myself because then I can pursue my career at the company.
Item 15	ILQ01[SQ0015]	I want to learn something new for myself because then I can solve problems at work faster.

6. **Social Interactions/Knowledge Sharing with Colleagues** (KSBS – Knowledge Sharing Behavior Scale (https://doi.org/10.1057/kmrp.2008.36))		
Item	**Question code**	**Question**
Written contributions		
Item 3	WrittQ01[SQ001]	I share documentation from personal files related to current work.
Item 4	WrittQ01[SQ002]	I contribute ideas and thoughts to a company online database.
Organizational communications		
Item 1	OrgQ01[SQ001]	I express ideas and thoughts in organizational meetings.
Item 2	OrgQ01[SQ002]	I engage in long-term coaching relationships with junior employees.
Item 3	OrgQ01[SQ003]	I spend time in personal conversation (e.g., discussion in hallway, over lunch, through call) with others to help them with their work-related problems.
Item 4	OrgQ01[SQ004]	I keep others updated with important organizational information through personal conversation.
Item 5	OrgQ01[SQ005]	I share passion and excitement on some specific subjects with others through personal conversation.
Item 6	OrgQ01[SQ006]	I share experiences that may help others avoid risks and trouble through personal conversation.
Item 7	OrgQ01[SQ007]	I have online chats with others to help them with their work-related problems.
Item 8	OrgQ01[SQ008]	I spend time in e-mail communication with others to help them with their work-related problems.
Communities of practice		
Item 1	CommQ01[SQ001]	I meet with community* members to create innovative solutions for problems that occur in work.
Item 2	CommQ01[SQ002]	I meet with community members to share own experience and practice on specific topics with common interests.
Item 3	CommQ01[SQ003]	I meet with community members to share success and failure stories on specific topics with common interests.
Item 4	CommQ01[SQ004]	I meet with community members to work to encourage excellence in community's practice.

Item 5	CommQ01[SQ005]	I support personal development of new community members.
Item 6	CommQ01[SQ006]	I send related information to members through community e-mail list.
Item 7	CommQ01[SQ007]	I share ideas and thoughts on specific topics through company supported online community-of-practice system.

7. **Adoption and Attitudes Towards AI in Learning** (TAM – Technology Acceptance Model (Davis, 1989))		
Item	**Question code**	**Question**
Perceived Ease-of-Use		
Item 7	PEUQ01[SQ001]	Learning to use LLMs is easy for me.
Item 8	PEUQ01[SQ002]	I find it easy to get LLMs to do what I want it to do.
Item 9	PEUQ01[SQ003]	My interaction with LLMs is clear and understandable.
Item 10	PEUQ01[SQ004]	I find LLMs to be clear and understandable.
Item 11	PEUQ01[SQ005]	It is easy for me to become skillful at using LLMs.
Item 12	PEUQ01[SQ006]	I find LLMs easy to use.
8. **Perceived Effects on Productivity and Learning Outcomes** (TAM)		
Perceived Usefulness		
Item 1	PUQ01[SQ001]	Using LLMs in my job enables me to accomplish tasks more quickly.
Item 2	PUQ01[SQ002]	Using LLMs improves my job performance.
Item 3	PUQ01[SQ003]	Using LLMs in my job increases my productivity.
Item 4	PUQ01[SQ004]	Using LLMs enhance my effectiveness on the job.
Item 5	PUQ01[SQ005]	Using LLMs makes it easier to do my job.
Item 6	PUQ01[SQ006]	I find LLMs useful in my job.
Item 7	PUQ01[SQ007]	I trust the information generated by LLMs in my job.

9. **Open-ended Questions (Qs from "AI and science: what 1,600 researchers think" – nature, 2023)**		
Item	**Question code**	**Question**
Item 15	OpenQ01	What's the most impressive or useful example of AI tools in your environment that comes to your mind?

Item 16	OpenQ02	What's the most concerning example of AI in your environment that comes to your mind?

Participants

- Total number of analyzed participants: 33
  - of which male: 18 (54.55%)
  - of which female: 15 (45.45%)
- Age: mean 31.85, std 11.03
- Work of field distribution:
  - Information Technology: 39.39%
  - Finance/Banking: 12.12%
  - Engineering/Tech Industry: 12.12%
  - Social Sciences/Psychology: 9.09%
  - Media / Creative Arts: 9.09%
  - Fishing / Fish Industry: 6.06%
  - Business / Management: 6.06%
  - Chemical Industry: 3.03%
  - Fashion: 3.03%
- Main occupation distribution
  - Employee: 45.45%
  - Student: 45.45%
  - Self-employed: 6.06%
  - Academic: 3.03%

Correlation Matrix

	gender	age	studyPFtime	workPFtime	yearsWorkExp	timeInPosition	hierarchy	sizeTeam	responsibility
gender	***1.00***	0.08	-0.15	-0.01	0.10	-0.01	0.17	0.28	0.05
age	0.08	***1.00***	***-0.51***	***0.44***	***0.96***	***0.92***	***0.82***	0.11	***0.39***
studyPFtime	-0.15	***-0.51***	***1.00***	***-0.80***	***-0.44***	***-0.41***	***-0.52***	-0.09	***-0.37***
workPFtime	-0.01	***0.44***	***-0.80***	***1.00***	***0.39***	0.36	***0.45***	0.14	***0.36***
yearsWorkEx	0.10	***0.96***	***-0.44***	***0.39***	***1.00***	***0.91***	***0.84***	0.21	0.35
timeInPositic	-0.01	***0.92***	***-0.41***	0.36	***0.91***	***1.00***	***0.81***	0.09	***0.43***
hierarchy	0.17	***0.82***	***-0.52***	***0.45***	***0.84***	***0.81***	***1.00***	0.08	***0.49***
sizeTeam	0.28	0.11	-0.09	0.14	0.21	0.09	0.08	***1.00***	0.02
responsibility	0.05	***0.39***	***-0.37***	***0.36***	0.35	***0.43***	***0.49***	0.02	***1.00***
AI_Lit	0.13	-0.36	0.26	-0.14	***-0.38***	-0.35	***-0.39***	-0.06	-0.09
frequency	0.01	-0.32	0.19	-0.17	***-0.37***	***-0.36***	***-0.45***	-0.18	-0.23
llmTaskComp	-0.33	0.26	-0.09	0.10	0.20	0.29	-0.03	0.05	0.12
colleagueTas	-0.32	-0.14	0.10	0.04	-0.01	-0.04	0.07	0.11	0.25
IL_Non_LLM	-0.19	0.04	-0.12	0.23	0.11	-0.02	0.13	0.20	0.36
IL_LLM	0.15	-0.22	-0.01	0.01	-0.27	-0.29	-0.34	-0.06	-0.05
writtenContr	0.04	-0.22	-0.13	***0.36***	-0.25	-0.27	-0.07	0.08	0.11
orgComms	-0.14	0.10	-0.34	***0.39***	0.13	0.11	0.22	0.13	***0.66***
communCon	-0.08	0.30	***-0.40***	0.25	0.30	0.20	0.26	0.26	***0.46***
pEU	0.25	-0.29	0.10	-0.09	-0.28	-0.24	-0.31	0.09	-0.13
pUse	0.09	-0.09	0.05	-0.06	-0.09	-0.04	-0.13	-0.14	-0.15
interviewtim	0.18	***0.43***	-0.16	0.15	***0.51***	0.20	0.25	0.29	-0.18

	AI_Lit	frequency	llmTaskComp	colleagueTas	IL_Non_LLM	IL_LLM	writtenContr	orgComms	communCon	pEU	pUse	interviewtim
gender	0.13	0.01	-0.33	-0.32	-0.19	0.15	0.04	-0.14	-0.08	0.25	0.09	0.18
age	-0.36	-0.32	0.26	-0.14	0.04	-0.22	-0.22	0.10	0.30	-0.29	-0.09	***0.43***
studyPFtime	0.26	0.19	-0.09	0.10	-0.12	-0.01	-0.13	-0.34	***-0.40***	0.10	0.05	-0.16
workPFtime	-0.14	-0.17	0.10	0.04	0.23	0.01	***0.36***	***0.39***	0.25	-0.09	-0.06	0.15
yearsWorkEx	***-0.38***	***-0.37***	0.20	-0.01	0.11	-0.27	-0.25	0.13	0.30	-0.28	-0.09	***0.51***
timeInPositic	-0.35	***-0.36***	0.29	-0.04	-0.02	-0.29	-0.27	0.11	0.20	-0.24	-0.04	0.20
hierarchy	***-0.39***	***-0.45***	-0.03	0.07	0.13	-0.34	-0.07	0.22	0.26	-0.31	-0.13	0.25
sizeTeam	-0.06	-0.18	0.05	0.11	0.20	-0.06	0.08	0.13	0.26	0.09	-0.14	0.29
responsibility	-0.09	-0.23	0.12	0.25	0.36	-0.05	0.11	***0.66***	***0.46***	-0.13	-0.15	-0.18
AI_Lit	***1.00***	***0.71***	0.13	0.04	-0.23	***0.61***	-0.11	0.04	-0.19	***0.78***	***0.68***	-0.13
frequency	***0.71***	***1.00***	***0.37***	-0.11	-0.27	***0.62***	-0.02	-0.11	-0.06	***0.50***	***0.62***	0.02
llmTaskComp	0.13	***0.37***	***1.00***	-0.16	-0.08	0.29	-0.23	0.01	0.03	0.20	0.23	0.12
colleagueTas	0.04	-0.11	-0.16	***1.00***	0.32	-0.12	0.10	***0.45***	0.34	-0.07	0.06	-0.12
IL_Non_LLM	-0.23	-0.27	-0.08	0.32	***1.00***	0.03	0.05	***0.52***	***0.39***	-0.12	-0.22	0.10
IL_LLM	***0.61***	***0.62***	0.29	-0.12	0.03	***1.00***	-0.06	0.08	0.06	***0.55***	***0.52***	0.14
writtenContr	-0.11	-0.02	-0.23	0.10	0.05	-0.06	***1.00***	0.30	0.09	-0.17	-0.30	-0.14
orgComms	0.04	-0.11	0.01	***0.45***	***0.52***	0.08	0.30	***1.00***	***0.60***	0.03	-0.11	-0.06
communCon	-0.19	-0.06	0.03	0.34	***0.39***	0.06	0.09	***0.60***	***1.00***	-0.25	-0.10	0.22
pEU	***0.78***	***0.50***	0.20	-0.07	-0.12	***0.55***	-0.17	0.03	-0.25	***1.00***	***0.59***	-0.08
pUse	***0.68***	***0.62***	0.23	0.06	-0.22	***0.52***	-0.30	-0.11	-0.10	***0.59***	***1.00***	-0.06
interviewtim	-0.13	0.02	0.12	-0.12	0.10	0.14	-0.14	-0.06	0.22	-0.08	-0.06	***1.00***

All correlations above $r_{critical} = 0.344$

Variable 1	**Variable 2**	**Correlation**
age	yearsWorkExp	0.96
age	timeInPosition	0.92
yearsWorkExp	timeInPosition	0.91
yearsWorkExp	hierarchy	0.84
age	hierarchy	0.82
timeInPosition	hierarchy	0.81
AI_Lit	pEU	0.78
AI_Lit	frequency	0.71
AI_Lit	pUse	0.68
responsibility	orgComms	0.66
frequency	IL_LLM	0.62
frequency	pUse	0.62
AI_Lit	IL_LLM	0.61
orgComms	communContr	0.60
pEU	pUse	0.59
IL_LLM	pEU	0.55
IL_Non_LLM	orgComms	0.52
IL_LLM	pUse	0.52
yearsWorkExp	interviewtime	0.51
frequency	pEU	0.50
hierarchy	responsibility	0.49
responsibility	communContr	0.46
colleagueTaskComplexity	orgComms	0.45
workPFtime	hierarchy	0.45
age	workPFtime	0.44
timeInPosition	responsibility	0.43
age	interviewtime	0.43
workPFtime	yearsWorkExp	0.39
workPFtime	orgComms	0.39
age	responsibility	0.39
IL_Non_LLM	communContr	0.39
frequency	llmTaskComplexity	0.37
workPFtime	responsibility	0.36
workPFtime	writtenContribution	0.36
responsibility	**IL_NON_LLM**	**0.36**
workPFtime	**timeInPosition**	**0.36**
yearsWorkExp	**responsibility**	**0.35**

timeInPosition	**AI_Lit**	**-0.35**
age	**AI_Lit**	**-0.36**
timeInPosition	frequency	-0.36
yearsWorkExp	frequency	-0.37
studyPFtime	responsibility	-0.37
yearsWorkExp	AI_Lit	-0.38
hierarchy	AI_Lit	-0.39
studyPFtime	communContr	-0.40
studyPFtime	timeInPosition	-0.41
studyPFtime	yearsWorkExp	-0.44
hierarchy	frequency	-0.45
age	studyPFtime	-0.51
studyPFtime	hierarchy	-0.52
studyPFtime	workPFtime	-0.80

Github-Repo for Analysis

https://github.com/david-747/WISTS_Study