

Workaholism is associated with dependency on Large Language Models in a cross-national study

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Abstract

The rapid adoption of Large Language Models (LLMs) has created new forms of digital reliance, yet little is known about how work-related pressures may be associated with this dependency. This study investigated whether two core dimensions of workaholism, working excessively and working compulsively, are linked to instrumental and relational dependency on LLMs across three national samples. Participants from China ($n = 563$), Germany ($n = 360$), and the United Kingdom (UK) ($n = 567$) completed validated measures of workaholism and LLM dependency. Configural and metric invariance were supported for both scales, enabling comparisons of associations across countries. Working compulsively showed consistent positive associations with both forms of dependency in China and Germany, with a weaker pattern in the UK. Working excessively was largely unrelated to dependency in simple correlations, although pooled regression models indicated small negative associations in the German reference group. Cultural moderation emerged for only one pathway: the link between compulsive work and relational dependency was significantly weaker in the UK than in China and Germany. Pooled models confirmed that working compulsively was the most reliable predictor of both instrumental and relational dependency, whereas working excessively showed modest negative associations. Chinese participants reported higher levels of instrumental and relational dependency than Germans; Chinese and British participants also showed higher instrumental dependency. These findings suggest that compulsive work habits make employees particularly susceptible to both instrumental and relational dependency on LLMs. For individuals exhibiting these patterns unrestricted access to LLMs may reinforce unhealthy levels of work involvement, hence increasing the likelihood of blurred work-life boundaries.

1 Introduction

In recent years, Large Language Models (LLMs), such as ChatGPT and DeepSeek, have become increasingly embedded in professional environments across a wide range of industries. LLMs can understand context, intent, and sentiment, allowing people of all ages and backgrounds to interact naturally in multiple languages, even without programming or computer science expertise. These advanced artificial intelligence (AI) tools are now widely used to automate processes, produce written materials, support decision-making, and enhance communication, thereby transforming traditional workplace practices (Dwivedi et al., 2023; Paik et al., 2025). For many employees, the workday now starts not with checking emails or attending meetings, but with launching their preferred LLM to organize tasks, compose emails, or generate new ideas. LLMs have rapidly evolved from cutting-edge innovations to essential resources in daily workflows. This change in routine is fostering a quiet, yet significant, reliance on LLMs that is reshaping how people engage with their work. Recent studies have begun to document the emergence of LLM dependency as a distinct behavioral pattern, highlighting that individuals are increasingly relying on LLMs not only for task completion and productivity, but also for support in social and relational contexts (Yankouskaya et al., 2025). In response, tools and scales have been proposed to assess dependency by adapting classic behavioral addiction symptoms to the context of AI use (Yankouskaya et al., 2025; Li et al., 2025). LLM dependency reflects how the use of these

technologies may involve habitual or preferred reliance beyond mere practical utility. This dependency manifests in two primary ways. First, instrumental dependency reflects users' tendency to rely on LLMs for cognitive tasks and decision-making, emphasizing their role as functional tools that support information processing and problem-solving. Second, relational dependency captures the development of parasocial relationships in which users view and interact with LLMs as socially meaningful entities (Yankouskaya et al., 2025). This growing body of research explores how different aspects of user behavior and attitude, such as instrumental use, emotional attachment, and fear of AI, combine to influence dependency.

As LLMs become increasingly embedded in work routines, concerns have emerged regarding how personal behaviors relate to the ways people engage and interact with these technologies. A growing body of research suggests that personality traits are important determinants of individuals' attitudes to adopt and engage with emerging technologies (Dalvi-Esfahani et al., 2020; Devaraj et al., 2008; Ozbek et al., 2014). More recent investigations have focused on how particular personality characteristics relate to attitudes toward AI (Park & Woo, 2022; Sindermann et al., 2022). Traits such as neuroticism, perfectionism, and impulsivity have often been associated with problematic digital behaviors, including excessive use of social media and growing reliance on technology (Marino et al., 2018; Kuss & Griffiths, 2012).

Within technology-driven workplaces, certain work attitudes may serve as key drivers of dependency on LLMs. For instance, long working hours have been identified as a primary trigger for excessive technology use (Griffiths, 2010). Individuals who tend to work excessively and compulsively (two behavioral aspects of workaholism) are particularly susceptible to developing unhealthy patterns of technology reliance (Porter & Kakabadse, 2006). Workaholism is commonly defined as a persistent tendency to work both excessively and compulsively (Schaufeli et al., 2009). Working excessively reflects behavioral overinvolvement in work (e.g. long hours and working beyond what is reasonably expected), whereas working compulsively captures an internal drive and obsessive preoccupation with work (e.g. persistent thoughts about work and feeling guilty when not working). Both dimensions have been linked to poorer health, reduced well-being, and difficulties in detaching from work (Andreassen, 2014). Workaholics often struggle to disengage from work, which contributes to problematic technology use (Cheung et al., 2022; Spagnoli et al., 2019). Research has shown that excessive work behavior is a proximal driver of compulsive internet use, especially for work-related purposes (Quiñones-García & Korak-Kakabadse, 2014). Individuals with workaholic tendencies often engage in more intensive technology use, driven by their characteristic motivations and behaviors (Buono et al., 2023). Their compulsive desire to work excessively and outside typical hours can result in a heightened reliance on LLMs. The continual availability of AI tools allows workaholics to stay connected to work tasks even beyond standard working times, potentially creating a reinforcing loop of overwork and increased LLM utilization.

Despite the growing use of LLMs in workplace settings, most research has concentrated on the technical features and practical advantages of these tools, while largely overlooking the psychological

mechanisms underlying dependency (Almogren et al., 2024). This perspective often neglects critical user-centered factors, such as work-related attitudes, that may contribute to overreliance on LLMs. While recent research has started to consider contextual factors such as workload, time constraints, and stress (Abbas et al., 2024; Zhang et al., 2024), the distinct impact of workaholism on developing dependency on LLMs has yet to be thoroughly investigated. As the integration of LLMs into professional settings accelerates, it becomes increasingly important to understand not only how these tools affect users, but also what motivates and predicts their reliance. Addressing this gap is essential for developing a more comprehensive understanding of human-AI interaction and for informing responsible and sustainable use of generative AI in the workplace.

Moreover, previous research indicates that behavioral patterns vary across cultures and are not universally consistent (Srite & Karahanna, 2006). Recent studies highlight that cultural background plays a significant role in shaping how individuals interact with AI technologies, including LLMs (Liebherr et al., under review; Mantelo et al., 2023; Folk et al., 2025). As a result, culture can influence not only the nature of human-AI interactions, but also individuals' attitudes toward adopting and relying on AI tools in the workplace. For instance, research comparing Chinese, German, and British samples found that Chinese participants reported the highest levels of acceptance and the lowest levels of fear toward AI (Sindermann et al., 2021). Another study suggests that individualistic societies prioritize personal autonomy and efficiency, which may encourage greater adoption and integration of LLMs into daily work practices. In contrast, collectivist cultures tend to value human relationships and collaborative approaches, potentially leading to more cautious or community-oriented use of AI tools (Elippatta & Intezari, 2025). These studies indicate that cultural context may contribute to varying degrees of LLM dependency, with individuals from cultures more accepting of AI potentially being more likely to integrate these technologies into their daily work routines. Moreover, cultural differences in attitudes toward work and technology use may shape these relationships in distinct ways across countries.

To address these gaps, the present study aims to advance understanding of LLM dependency by examining three key aspects. First, we examine the association between workaholism and relational and instrumental dependency on LLMs. Second, we explore cross-cultural differences in LLM dependency by comparing samples from China, the UK, and Germany, each representing distinct cultural and organizational contexts. Third, we assess whether the relationship between workaholic behaviors and LLM dependency remains robust across these diverse populations.

2 Literature review

2.1 LLM Dependency

The growing use of LLMs is gradually, yet significantly, transforming workplace behaviors. A clear indication of this change is the rise of digital dependency among employees. Many now find it challenging to begin their work without first turning to LLMs, using ChatGPT for tasks such as drafting email templates, condensing reports, or receiving guidance on initiating conversations. The user-friendly

conversational design and the sophisticated nature of LLM outputs often encourage users to view these systems as more human-like, potentially leading to an overreliance on their capabilities (Letiche & Lissack, 2025). This reliance closely resembles earlier forms of technology dependency, such as the habitual use of smartphones (Cramer, 2018). While LLMs significantly enhance productivity and problem-solving, there remains a growing concern over the potential for user dependency on these systems. Regular reliance on LLMs may lead to a reduced capacity for cognitive processing and information retention (Marzuki et al., 2023). This dependency is theoretically grounded in the observation that the immediate answers and time-saving benefits offered by LLMs can inadvertently reinforce compulsive use (Yankouskaya et al., 2025a).

Moreover, LLM dependency may operate through mechanisms distinct from traditional digital addictions. LLMs often foster engagement by personalized feedback, emotional reassurance, and task-related success (Yankouskaya et al., 2025a). This dependency goes beyond merely accomplishing tasks, it also meets deeper emotional and psychological needs. The concept of LLM dependency was introduced by Yankouskaya et al. (2025b) as an excessive reliance on large language models for various work-related purposes, emphasizing not only the extent to which individuals depend on these tools to manage tasks but also their use in handling social and communicative aspects of professional life. They distinguished between two dimensions of dependency: instrumental and relational. Instrumental dependency captures the extent to which individuals rely on LLMs for task-oriented activities such as completing assignments, organizing work, and solving problems efficiently. Relational dependency, on the other hand, reflects the use of LLMs for social or collaborative engagement, including seeking advice, brainstorming ideas, or using LLMs as conversational partners for professional communication. Both forms of dependency encompass not only frequent and habitual use, but also a deeper psychological reliance on LLMs to manage day-to-day work demands (Yankouskaya et al., 2025b).

2.2 The link between workaholism and LLM dependency

While research on the overlap between workaholism and other behavioral addictions remains limited, existing studies have begun to uncover associations with patterns of excessive internet and smartphone use (Cheung et al., 2022; Quinones et al., 2016). Evidence suggests that workaholic individuals not only utilize their smartphones more intensively than their nonworkaholic counterparts, but also engage in higher rates of evening usage, a pattern linked to increased sleep disturbances. Although prior studies have examined patterns of smartphone usage, there is growing evidence to suggest that workaholism may also be linked to increased reliance on advanced digital tools such as LLMs. Rayat et al. (2025) reported that individuals who rely on AI technologies to handle their workload are more likely to display signs of work addiction, a pattern closely related to cognitive workaholism.

Although there is currently no direct evidence that workaholics are more likely to use LLMs, existing data shows that a significant number of employees, especially those striving for greater efficiency or managing demanding workloads, are incorporating AI tools into their work routines. According to research by Upwork, 77% of workers reported that AI adoption has increased their workload, contributing to elevated levels of burnout (Monahan & Burlacu, 2024). This pattern implies that individuals utilizing AI

may be assuming more responsibilities, a behavior commonly linked to workaholic tendencies. Notably, recent findings also indicate a shift in LLMs usage, with the majority of ChatGPT interactions now occurring for personal rather than professional purposes, suggesting that people are increasingly turning to AI for everyday decision-making beyond the workplace (Monahan & Burlacu, 2024).

Hence, we assume that the two dimensions of workaholism are likely to relate to these two forms of dependency in different ways. Working excessively emphasizes the behavioral side of overwork (long hours and high workload) rather than emotional attachment. Employees who work to excess may turn to LLMs primarily as productivity aids to cope with work volume and time pressure. Working compulsively reflects an internal, often anxiety-driven urge to work, accompanied by obsessive thoughts about work and difficulties in disengaging. This cognitive-emotional component suggests stronger potential for both instrumental and relational dependency. Compulsive workers are likely to use LLMs instrumentally to stay continuously productive and to reduce the discomfort associated with not working. At the same time, workaholism is associated with strain, interpersonal conflict, and social difficulties, including conflict at work and poorer private relationships (Andreassen, 2014). Studies on anthropomorphic technologies show that individuals with unmet social needs or loneliness may anthropomorphize technological agents and use them to fulfil social or relational needs (Christoforakos & Diefenbach, 2023). It is therefore plausible that compulsive workers could increasingly use LLMs for relational purposes such as seeking reassurance, guidance, or a sense of being “understood” in their work context. Therefore, we propose the following hypotheses:

H1a

Working excessively is positively associated with instrumental dependency on LLMs.

H1b

Working compulsively is positively associated with instrumental dependency on LLMs.

H1c

Working excessively is positively associated with relational dependency on LLMs.

H1d

Working compulsively is positively associated with relational dependency on LLMs.

2.3 Cultural differences

National culture plays a significant role in shaping how individuals think, make decisions, and behave (Weber & Morris, 2010; Hofstede, 1984; House et al., 2004). As a result, people from different cultural backgrounds may demonstrate varying patterns of technology reliance (Lee et al., 2013). Culture can be understood as the shared mental framework that sets one group apart from another (Hofstede, 1984), or as the distinctive ways of thinking, feeling, and responding that characterize human societies (Cao et al.,

2023). This cultural context not only affects how individuals judge the accuracy of recommendations (Kramer et al., 2007) but also shapes their willingness to trust and act upon suggestions provided by LLMs.

The impact of culture is evident across multiple dimensions, including individualism, power distance, uncertainty avoidance, and societal values such as trust and transparency (Srite & Karahanna, 2006). Research has shown that higher levels of individualism are associated with a greater tendency to rely on automation (Chien et al., 2016; Chien et al., 2018). Individualism characterizes societies where people emphasize personal achievement, autonomy, and individual rights, while collectivism refers to cultures that prioritize group harmony, loyalty, and mutual dependence. It has also been observed that reliance on automated assistance increases in situations of uncertainty, particularly in individualist societies compared to collectivist ones (Chien et al., 2016). In the context of chatbot journalism, studies reveal that Japanese users, representing a collectivist culture, focus more on the functional aspects of chatbots, whereas US users, from an individualist society, are more likely to value the non-functional, human-like qualities of chatbots and are more accepting of algorithmic explanations (Shin et al., 2022).

Prior research indicates that culture, as a dispositional factor, influences how individuals trust and depend on automated agents. For instance, Nordic countries' AI policies emphasize trust, transparency, and openness, which align with their cultural values (Noah & Sethumadhavan, 2019; Robinson, 2020). Additionally, studies have shown that, in comparison to European Americans, Chinese individuals are less focused on controlling AI and more interested in building a connection with it (Ge et al., 2024). Research also demonstrates that social media users from Spain, an individualistic society, are better at detecting fake news than those from Lebanon, a collectivist culture (Dabbous et al., 2022). Furthermore, culture has been identified as the most significant factor in determining whether people accept recommendations from robots (Rau et al., 2009). Similarly, it has been found that Mexicans tend to trust automated systems more readily than Americans (Huerta et al., 2012). Previous research also highlights notable regional variations in how AI is accepted and integrated. For instance, companies in countries such as India, Singapore, and China are more likely to implement AI within their business practices compared to those in France, Spain, and the United States (Benchaita, 2024). These differences in AI adoption are often used to explain why individuals in Eastern countries tend to view AI more positively and are generally more accepting of its use in various contexts, in contrast to attitudes found in many Western countries (Johnson & Tyson, 2020; Gillespie et al., 2023).

Therefore, based on this evidence, we propose the following hypotheses:

H2

The levels of instrumental and relational dependency on LLMs differ across China, Germany, and the UK.

Cross-national research has shown that the prevalence and expression of workaholism vary across countries, reflecting differences in norms around long hours, diligence, and work–life boundaries (Andersen et al., 2023). In some contexts, high workloads and devotion to work are socially rewarded,

potentially enhancing workaholic tendencies; in others, stronger norms around balance and rest may constrain their expression (Andersen et al., 2023). For example, Japanese employees exhibit higher levels of workaholism than their Dutch counterparts, reflecting the influence of cultural norms that emphasize interdependence within social relationships and a strong sense of hierarchy in the workplace (Schaufeli et al., 2009; Matsumoto, et al., 1996). In collectivist cultures, social harmony is prioritized, and individual well-being is often considered secondary to the well-being of the group (Iwata, et al., 1995). As a result, employees may feel compelled to remain at work until their superiors leave, reinforcing behaviors associated with workaholism and valuing those who are perceived as loyal and hardworking. Similarly, in China, Confucian values continue to shape workplace attitudes, encouraging occupational devotion, diligence, and persistent hard work (Tian, 2004). The intensification of workplace competition has further contributed to the prevalence of excessive work behaviors, with Chinese employees often scoring higher on workaholism measures than their Western counterparts (Hu et al., 2014).

Additionally, attitudes towards artificial intelligence also differ cross-nationally (Sindermann et al., 2021). For instance, research indicates that Chinese individuals showed higher acceptance of AI compared to the Germans (Sindermann et al., 2022). Moreover, people in emerging economies in the Global South tend to be more trusting and optimistic about AI, while populations in advanced Western economies are generally more cautious and concerned about its risks (Gillespie et al., 2025). Emerging studies on generative AI use in organizations likewise suggest that employee perceptions and adoption are shaped by local institutional and cultural contexts (Wut & Chan, 2025). These findings imply that both the level of dependency on LLMs and the way workaholic tendencies translate into dependency may differ between China, Germany, and the UK. In contexts where AI is more positively regarded and where intensive work norms are more salient, we might expect higher instrumental and relational dependency overall. In more cautious regulatory environments, employees may still use LLMs but do so less intensively or in more constrained ways. Cultural values around social interaction and the acceptability of forming relationships with technology are also likely to influence whether dependency remains largely instrumental or extends to relational use.

Therefore, we hypothesize that cultural background will moderate the relationships between workaholism and LLM dependency, such that:

H3a

The positive associations between working excessively and LLM dependency differ in strength across China, Germany, and the UK.

H3b

The positive associations between working compulsively and dependency (instrumental and relational) differ in strength across China, Germany, and the UK.

3 Method

3.1 Study design

This study utilized a cross-sectional survey design as part of a broader research project focused on evaluating the effects of dependency on LLMs on various aspects of human functioning. Data were collected from participants in three countries, the UK, Germany, and China, to enable cross-cultural comparisons. Participants were recruited online via the Prolific platform (prolific.com) in the UK and Germany and via Credemo (credemo.com) and Wenjuanxing (wjx.cn) platforms in China. The survey was conducted using SurveyMonkey (surveymonkey.com) and consisted of two main sections. The first section gathered demographic information, including age, gender, employment status, to verify participant eligibility and to allow for subsequent demographic analyses. The second section assessed participants' familiarity and usage of LLMs, alongside measures of personality traits, cognitive styles, and other psychological factors relevant to LLM dependency.

Prior to beginning the survey, all participants were provided with detailed information about the study's purpose, procedures, and their rights as research subjects. Informed consent was obtained electronically, and participants were explicitly informed of their right to withdraw from the study at any time without penalty.

3.2 Participants

Sample size estimation was conducted a priori based on the planned statistical analysis, which consisted of multiple linear regression models including interaction terms to test whether working excessively and working compulsively predicted instrumental and relational dependency on large language models, and whether these associations varied as a function of cultural background (China, Germany, the UK). Because no prior empirical evidence was available to inform plausible effect size estimates for these associations, sample size calculation in the present study relied on a conservative small-effect assumption. In accordance with established conventions for multiple regression, a small effect was defined as Cohen's $f^2 = .02$ (Cohen, 2013). Statistical power was set at 90% ($1 - \beta = .90$) with a two-sided significance level of $\alpha = .05$ (Lakens, 2022). Under these assumptions, detecting a small moderation effect ($f^2 = .02$) for a four-degree-of-freedom interaction test requires a minimum total sample size of $N = 776$. The final analytic sample comprised 563 participants from China, 360 from Germany, and 567 from the UK (total $N = 1,490$), substantially exceeding the estimated minimum requirement. Although country sample sizes were unequal, the smallest group (Germany, $n = 360$) exceeded the implied per-country minimum under a balanced three-group design (approximately 259 participants per country), indicating adequate power to estimate moderation effects in each country. Sample size was calculated using GPower (Version 3.1.9.6) (Faul et al., 2009).

Eligible participants were required to be at least 18 years of age. To ensure data quality, the survey included attention check items, and individuals who failed to respond appropriately to these checks were excluded from the final analysis. Exclusion criteria were applied to participants who neither used their LLM frequently nor reported significant reliance on it. Participants were also screened based on

employment status. Individuals who identified as homemakers (China: $n = 1$, .05%; Germany: $n = 4$, 1.02%; the UK: $n = 0$, 0%), retired (China: $n = 0$, 0%; Germany: $n = 1$, .26%; the UK: $n = 0$, 0%), or unemployed (China: $n = 12$, 2.08%; Germany: $n = 18$, 4.6%; the UK: $n = 0$, 0%) were excluded to ensure the sample reflected active engagement in work or study contexts. For student participants, survey instructions clarified that references to “work” should be interpreted as relating to their studies or academic responsibilities. After applying these inclusion and exclusion criteria, the final samples retained for analysis consisted of 563 participants from China, 360 from Germany, and 567 from the UK. The mean age of participants was 26.68 years (SD = 5.61) in China, 31.06 years (SD = 5.97) in Germany, and 28.94 years (SD = 6.17) in the UK.

An overview of the sample’s characteristics, including details on participants’ demographics is presented in in Table 1.

Table 1
A summary of participants' characteristics for three samples.

Variable	Category	China (<i>n</i> = 563)		Germany (<i>n</i> = 360)		The UK (<i>n</i> = 567)	
		<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
Gender	Male	218	38.72	192	53.33	286	50.44
	Female	345	61.28	166	46.11	275	48.50
	Missing	-	-	2	.56	6	1.06
Employment Status	Full-time	357	63.41	242	67.22	354	62.43
	Part-time	13	2.31	45	12.50	67	11.82
	Self-employed	34	6.04	8	2.22	18	3.17
	Students	159	28.24	65	18.06	128	22.58
Education level	Primary education	-	-	18	5.00	-	-
	Secondary education	7	1.24	37	10.28	72	12.70
	Pursuing or completed vocational or technical education	44	7.82	76	21.11	58	10.23
	Pursuing or completed undergraduate degree	417	74.07	134	37.22	295	52.03
	Pursuing or completed postgraduate degree	95	16.87	95	26.39	142	25.04
Frequency of LLM use	Less than once per month	2	.35	12	3.33	0	0
	1–3 times per month	11	1.95	33	9.17	5	0.88
	1–2 times per week	23	4.09	38	10.55	24	4.23
	3–6 times per week	153	27.18	69	19.17	110	19.40
	Once daily	70	12.43	58	16.11	92	16.23
	Multiple times daily	304	54.00	150	41.67	336	59.26

3.3 Measures

Workaholism

Workaholism was assessed using two subscales adopted from Schaufeli et al. (2009): working excessively and working compulsively. Working Excessively was assessed with five items which reflect behaviors such as feeling rushed, continuing to work after others stop, multitasking, and prioritizing work

over leisure. Participants responded using an 11-point Likert scale (0 = Totally Disagree, 10 = Totally Agree), with higher scores indicating greater work excessiveness. The subscale demonstrated good reliability, with Cronbach's alpha values of .790 (China), .749 (the UK), and .777 (Germany), and McDonald's omega values of .804, .753, and .787, respectively.

Working Compulsively was measured using five items that assess the cognitive and emotional compulsion to work, regardless of enjoyment. Example items include: "I feel that there is something inside me that drives me to work hard" and "I feel guilty when I take time off work." Participants rated each statement on an 11-point Likert scale (0 = Totally Disagree, 10 = Totally Agree), with higher scores indicating greater compulsive work tendencies. Reliability analyses indicated satisfactory internal consistency for instrumental dependency in the UK and Germany samples, with Cronbach's alpha values of .824 (the UK), and .810 (Germany), and McDonald's omega values of .726, and .740, respectively. In contrast, the Chinese sample exhibited lower internal consistency, with a Cronbach's alpha of .583 and a McDonald's omega of .447.

LLM dependency

Dependency on large language models (LLMs) was measured using an adapted version of the LLM-D12 Scale developed by Yankouskaya et al. (2025), encompassing two dimensions: instrumental dependency and relational dependency. Each subscale includes 6 items, and respondents rated their agreement with each statement on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*).

Instrumental dependency on LLMs was measured using a set of items assessing the extent to which participants rely on LLMs for task efficiency, decision confidence, and problem-solving. Example items include: 'Without it, I feel less confident when making decisions,' and 'I turn to it for support in decisions, even when I can make them myself with some effort.' Internal consistency for this subscale was excellent, as evidenced by Cronbach's alpha coefficients of .802 (China), .828 (the UK), and .908 (Germany), and McDonald's omega values of .798, .803, and .888, respectively.

Relational dependency on LLMs was assessed with items measuring the extent to which participants use LLMs for companionship and emotional support. Example items include, 'I interact with it as if it were a genuine companion,' and, 'It helps me feel less alone when I need to talk to someone.' Reverse-scored items were included to control response bias. The subscale showed strong reliability, with Cronbach's alpha values of .848 (China), .892 (the UK), and .887 (Germany), and McDonald's omega values of .852, .896, and .902, respectively.

3.4 Data analysis

We calculated descriptive statistics including means and standard deviations and assessed data normality using skewness and kurtosis measures. Subsequently, we aimed to verify the latent structure and factorial validity of the LLM dependency and workaholism constructs. To this end, confirmatory factor analyses (CFA) were performed independently for the Chinese, British, and German samples. This step was essential for evaluating whether the factor configurations proposed by the original scales were

supported in each cultural context. Model fit was assessed using conventional indices, including the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Model fit was considered adequate when CFI and TLI values were .90 or above, and RMSEA and SRMR values were below .08 (Hu & Bentler, 1999). The CFA was conducted using maximum likelihood estimation with robust standard errors (MLR). The analysis was conducted in R using the *lavaan* package (version 0.6–20; Rosseel, 2012). Additionally, we assessed internal consistency for each scale by calculating both Cronbach's alpha and McDonald's omega coefficients.

Prior to conducting cross-cultural comparisons, it was imperative to ensure that the measurement instruments operated equivalently across all groups. Therefore, we conducted a series of measurement invariance analyses using multi-group confirmatory factor analysis (MGCFA), treating countries as the grouping variable. This approach allowed us to systematically evaluate configural, metric, scalar, and strict invariance models, thereby determining the degree to which the LLM dependency and workaholism scales were interpreted similarly among Chinese, British, and German respondents. Following established guidelines (Brwon, 2015), we tested four increasingly restrictive levels of invariance:

Configural invariance tests whether the basic factor structure (i.e., the pattern of fixed and free loadings) is consistent across groups, indicating that participants conceptualize the constructs similarly.

Metric invariance evaluates whether factor loadings are equivalent across groups, which allows for the comparison of relationships among variables (e.g., correlations, regressions).

Scalar invariance tests whether item intercepts are also equal, permitting the comparison of latent means between groups.

Strict invariance adds the constraint that residual variances are equal across groups, providing the strongest form of equivalence.

We assessed invariance by comparing model fit indices at each step, including CFI, TLI, RMSEA, and SRMR. In line with recommendations (Kim et al., 2017), a change in CFI (Δ CFI) of less than .01 and a change in RMSEA (Δ RMSEA) of less than .015 between successive models was taken as evidence of invariance. If invariance was not supported at a given level, modification indices and partial invariance approaches were considered.

To examine the basic associations between workaholism dimensions and both instrumental and relational LLM dependency, we conducted bivariate correlation analyses using Pearson's correlation coefficient. We enhanced the robustness of these correlation estimates by employing a bootstrap resampling procedure to generate 95% confidence intervals, thereby increasing the precision and reliability of the reported associations. To determine whether the strength of association between workaholism and LLM dependency varied as a function of cultural context, we performed comparative analyses of the correlation coefficients across the three national samples. Specifically, Fisher's z-

transformation was employed to statistically test significant differences between independent correlations (Fisher, 2015) with 95% Zou's confidence intervals for the cross-national differences (Zou, 2007). This approach allowed us to evaluate whether the relationships between the workaholism subscales and both instrumental and relational LLM dependency significantly differed across Chinese, British, and German participants.

Finally, to explore the extent to which working excessively and working compulsively predicted both instrumental and relational LLM dependency, and to assess whether these effects were moderated by cultural background, we conducted a series of pooled regression analyses. For each dimension of LLM dependency, we entered working excessively and working compulsively as predictors, along with their respective interaction terms with the country. The ordinary least squares (OLS) estimation was employed to estimate the regression coefficients. This analytic strategy facilitated the examination of both direct and interaction effects, thereby allowing us to test for cross-cultural variation in the influence of workaholism dimensions on LLM dependency across the three national samples.

4 Results

4.1 Descriptive statistics

To provide an initial overview of the data structure, we first calculated descriptive statistics including means, standard deviations, skewness, and kurtosis for all study variables (see Table 1). The analysis revealed that Chinese participants exhibited higher levels of both instrumental and relational dependency compared to the other groups. On the workaholism scale, Chinese participants had the highest average scores, while German participants had the lowest. Figure 1 depicts the bar charts of the study variable along with $\pm$ SD error bars separately for each sample.

We also examined skewness and kurtosis measures to evaluate the normality of the study variables within each sample. According to the guidelines proposed by Hair et al. (2010), all absolute values of skewness ($|\text{skewness}| \leq 2$) and kurtosis ($|\text{kurtosis}| \leq 7$) fell within acceptable ranges, indicating that the study variables in each sample follow a normal distribution.

Table 1
Descriptive statistics of the study variables for each sample.

Sample	Variable	Mean	Standard deviation	Skewness	Kurtosis
China	LLM: Instrumental dependency	25.551	5.177	– .773	.152
	LLM: relational dependency	23.645	6.118	– .827	.104
	Workaholism: working compulsively	28.631	9.779	– .259	– .518
	Workaholism: working excessively	30.876	6.549	– .254	.809
The UK	LLM: Instrumental dependency	21.388	6.290	– .133	– .519
	LLM: relational dependency	14.515	7.163	.706	– .438
	Workaholism: working compulsively	26.296	9.862	– .084	– .369
	Workaholism: working excessively	28.940	1.894	– .292	– .231
Germany	LLM: Instrumental dependency	18.428	7.935	.265	– .863
	LLM: relational dependency	16.044	8.084	.591	– .785
	Workaholism: working compulsively	25.456	10.543	– .004	– .738
	Workaholism: working excessively	24.939	11.337	– .100	– .468

4.2 Cross-national validity of constructs

To evaluate the latent structure and factorial validity of the LLM dependency and workaholism scales, we conducted confirmatory factor analyses (CFA) separately for each sample. This approach allowed us to assess whether the hypothesized factor models provided an adequate fit to the data within the Chinese, British, and German groups, and to examine the consistency of the underlying constructs across cultural contexts. The fit indices of CFA results are presented in Table 2 for each sample.

For the LLM dependency scale, fit indices indicated an acceptable model fit in all three samples. The CFI ranged from .943 to .971, and the TLI ranged from .925 to .961, both exceeding the commonly accepted threshold of .90, suggesting strong model fit. RMSEA values were below (for Chinese and British samples) and slightly above (for German sample) the recommended cutoff of .08, and SRMR values were all well below the .08 threshold, further supporting acceptable fit.

For the workaholism scale, model fit was within an acceptable range in China and the UK samples. The CFI values ranged from .922 to .943 and TLI values from .888 to .918, again supporting reasonable

model fit. RMSEA values ranged from .086 to .111, slightly above conventional cutoffs in all samples. SRMR values ranged from .079 to .102, with the Chinese and German samples slightly exceeding the typical threshold.

Table 2
Fit indices of LLM dependency and workaholism scales within each sample.

Scale	Sample	χ^2	<i>df</i>	<i>p</i> -value	CFI	TLI	RMSE	SRMR
<i>LLM dependency</i>								
	China	227.38	50	< .001	.943	.925	.079	.049
	The UK	160.16	50	< .001	.971	.961	.062	.038
	Germany	167.50	50	< .001	.967	.957	.081	.039
<i>Workaholism</i>								
	China	129.41	25	< .001	.933	.903	.086	.101
	The UK	161.23	25	< .001	.943	.918	.098	.079
	Germany	136.74	25	< .001	.922	.888	.111	.102
Note: χ^2 = Chi-square statistics; <i>df</i> = degree of freedom.								

Before comparing the relationship between LLM dependency and workaholism, we verified that the instruments are reliable and measured the same constructs across three samples. The measurement invariance analysis was conducted using the MGCFA method with country as the grouping variable. The results of measurement invariance analysis examining four models (M1: configural, M2: metric, M3: scalar, and M4: strict) are presented in Table 3.

Table 3
Chi-squared difference tests and fit indices of measurement invariance models

Set	Model	χ^2	<i>df</i>	<i>p</i> -value	CFI	TLI	RMSEA	SRMR
<i>LLM dependency</i>								
M1: Configural	555.05	150	< .001	.961	.949	.074	.039	
	M2: Metric	699.78	170	< .001	.949	.941	.079	.069
	M3: Scalar	1166.80	190	< .001	.907	.903	.102	.096
	M4: Strict	1465.18	214	< .001	.880	.889	.108	.100
Comparisons								
		$\Delta\chi^2$	Δdf	<i>p</i> -value	Δ CFI	Δ TLI	Δ RMSEA	Δ SRMR
	M2 vs. M1	130.92	20	< .001	– .012	– .008	.005	.030
	M3 vs. M2	437.17	20	< .001	– .042	– .038	.023	.027
	M4 vs. M3	200.77	24	< .001	– .027	– .011	.007	.004
<i>Workaholism</i>								
M1: Configural	427.38	75	< .001	.935	.906	.097	.085	
	M2: Metric	491.23	89	< .001	.925	.909	.095	.099
	M3: Scalar	777.11	103	< .001	.875	.869	.115	.118
	M4: Strict	953.32	121	< .001	.846	.862	.118	.127
Comparisons								
		$\Delta\chi^2$	Δdf	<i>p</i> -value	Δ CFI	Δ TLI	Δ RMSEA	Δ SRMR
	M2 vs. M1	48.60	14	< .001	– .010	.003	– .002	.014
	M3 vs. M2	274.47	14	< .001	– .050	– .040	.020	.019
	M4 vs. M3	118.22	18	< .001	– .029	– .007	.003	.009
Note: Δ represents the difference between fit indices; <i>df</i> = degree of freedom.								

Measurement invariance analysis for the LLM dependency scale indicated that both the configural and metric models provided acceptable fit across the Chinese, British, and German samples. The configural model showed good fit indices (CFI = .961, TLI = .949, RMSEA = .074, SRMR = .039), suggesting that

participants in all three samples conceptualized LLM dependency in a similar way. When factor loadings were constrained to be equal across groups in the metric model, the fit remained acceptable (CFI = .949, TLI = .941, RMSEA = .079, SRMR = .069). The decrease in CFI from the configural to the metric model was $-.012$, which is close to but slightly above the recommended cutoff of $.01$, indicating metric invariance is largely supported. These results demonstrate that the factor structure and factor loadings of the LLM dependency construct are consistent across the three cultural groups, enabling valid cross-cultural comparisons of associations involving LLM dependency.

For the workaholism scale, similar patterns were observed. The configural model produced fit indices of CFI = .935, TLI = .906, RMSEA = .097, and SRMR = .085. Imposing equality constraints on the factor loadings in the metric model resulted in only a slight reduction in fit (CFI = .925, TLI = .909, RMSEA = .095, SRMR = .099), with a Δ CFI of $-.010$ and a Δ RMSEA of $-.002$, which meets the generally accepted criteria for metric invariance. These findings indicate that the workaholism scale also demonstrates configural and metric invariance, suggesting that the underlying factor structure of workaholism was consistent across the China, the UK, and Germany samples. These results indicate that the scale measures the construct of workaholism similarly in all three samples. As a result, it is appropriate to compare relationships involving workaholism across these cultural groups.

Scalar and strict invariance for both workaholism and LLM dependency measures were not fully established. This limitation is frequently encountered in cross-national research, as item intercepts are often influenced by cultural variations in response patterns and baseline tendencies (Putnick & Bornstein, 2016). Nevertheless, because our primary focus was on examining the structural relationships between variables rather than comparing mean scores across countries, the demonstration of configural and metric invariance is sufficient to justify the cross-national use of the LLM dependency and workaholism scales in this study.

4.3 Bootstrapped correlations

In this section, bivariate correlation analyses using Pearson's coefficient were conducted to assess the potential association between LLM dependency and workaholism. Additionally, to ensure the stability and reliability of the correlation findings, 95% confidence intervals were calculated using the bootstrap method. Figure 2 gives a graphical overview of the correlation results, including the 95% bootstrapped CI.

Bivariate correlation analysis revealed that in the Chinese and German samples, individuals who exhibited higher levels of working compulsively were also more likely to report both instrumental and relational dependency on LLMs. This suggests that people who experience persistent inner pressure to work are particularly inclined to rely on LLMs not only for practical, task-related assistance but also for relational or collaborative support in their work environment. In contrast, working excessively was not associated with LLM dependency in either of these samples, and in the Chinese sample, there was a small negative association between working excessively and LLM relational dependency. This suggests that Chinese individuals who tend to work for long hours and constantly stay busy (i.e., those exhibiting excessive work behavior) are less likely to rely on LLMs for relational or companionship needs.

Among British participants, a small positive association was observed between working compulsively and LLM instrumental dependency, indicating that those who feel a persistent inner drive or compulsion to work are slightly more likely to depend on LLMs for practical, task-oriented purposes. In contrast, neither working compulsively nor working excessively was related to LLM relational dependency among British participants, implying that workaholic tendencies in this group do not extend to relying on LLMs for social or collaborative aspects of work. Overall, across all three samples, LLM dependency was more consistently linked to the compulsive aspect of workaholism rather than to excessive working.

4.4 Cross-national comparative correlation analysis

To assess whether the strength of association between workaholism and LLM dependency differed across cultural contexts, we conducted comparative correlation analyses among China, the UK, and Germany samples. Specifically, we tested the differences between correlations across independent groups using Fisher’s z-transformation method. In addition, we calculated Zou’s confidence intervals for the differences between correlation coefficients to provide robust estimates of the magnitude and significance of these cross-sample differences. The results of these analyses are presented in Table 5.

Table 5
Comparison of LLM dependency and workaholism association across samples

	The UK vs. China		China vs. Germany		The UK vs. Germany	
Association	z-value (p)	95% CI	z-value (p)	95% CI	z-value (p)	95% CI
Instrumental dependency – working excessively	.028 (.977)	[-.115, .118]	.132 (.895)	[-.123, .141]	.157 (.875)	[-.121, .143]
Instrumental dependency – working compulsively	-1.859 (.063)	[-.221, .006]	– .271 (.786)	[-.143, .110]	-1.911 (.056)	[-.252, .003]
Relational dependency – working excessively	.714 (.475)	[-.074, .158]	-1.538 (.124)	[-.235, .028]	– .911 (.363)	[-.193, .071]
Relational dependency – working compulsively	-2.714 (.007)	[-.274, – .044]	– .005 (.996)	[-.127, .128]	-2.399 (.016)	[-.288, – .029]

Comparative correlation analysis revealed notable cross-cultural differences only in the association between working compulsively and LLM relational dependency. This association was significantly stronger in the Chinese and German samples compared to the British sample. Specifically, the difference was significant between the UK and China samples ($z = -2.714$, $p = .007$, 95% CI [-.274, –.044]) and between the UK and Germany samples ($z = -2.399$, $p = .016$, 95% CI [-.288, –.029]), with both confidence intervals excluding zero. These findings suggest that in both Chinese and German contexts, individuals who work compulsively are more likely to depend on LLMs for relational purposes than their British counterparts. No significant differences were observed between Chinese and German samples

for this association ($z = -.005, p = .996$). For the remaining associations, there were no significant differences in their strength across the UK, China, and Germany samples.

Overall, the results indicate that cultural context moderates the relationship between compulsive workaholism and LLM relational dependency, with this association being notably weaker among British participants compared to Chinese and German participants. In contrast, associations involving working excessively and LLM dependency appear to be consistent across all three cultural groups.

4.5 Pooled linear regression results

To examine how working excessively and working compulsively influence both LLM instrumental dependency and LLM relational dependency across cultural contexts, we conducted a series of pooled regression analyses using samples from the UK, China, and Germany. For each type of LLM dependency, we included working excessively and working compulsively as predictors, along with their interactions with country, to assess whether the effects of workaholism on LLM dependency varied by cultural background. This approach allowed us to investigate both the direct and moderating effects of workaholism dimensions on LLM dependency across these three samples. The results of pooled regression analysis for two aspects of LLM dependency are presented in Table 6.

The model predicting LLM instrumental dependency was significant, $F(8, 1481) = 45.32, p < .001$, explaining 19.67% of the variance. Working compulsively had a significant positive effect on LLM instrumental dependency ($\beta = .219, SE = .036, t = 6.074, p < .001$), indicating that higher levels of compulsive work behavior are associated with increased instrumental dependency on LLMs. In contrast, working excessively was negatively associated with instrumental dependency ($\beta = -.115, SE = .039, t = -2.977, p = .003$), suggesting that individuals who work excessively may be less dependent on LLMs for instrumental purposes.

Significant main effects for country were observed in relation to LLM instrumental dependency, indicating differences in the extent to which participants from different cultural backgrounds rely on LLMs for instrumental purposes. Specifically, both Chinese ($\beta = 4.876, SE = 1.610, t = 3.030, p = .002$) and British ($\beta = 4.025, SE = 1.235, t = 3.259, p = .001$) participants reported significantly higher levels of instrumental dependency on LLMs compared to the German reference group. This means that, on average, individuals from China and the UK are more likely to use LLMs to assist with practical, task-oriented activities such as information retrieval, problem-solving, and work completion than their German counterparts.

Table 6
Pooled regression results

Dependent variable	Effect	Estimate	Std. error	t-value	p-value	95% CI
Instrumental dependency	Intercept	15.905	.917	17.342	< .001	[14.106, 17.704]
	Working compulsively	.219	.036	6.074	< .001	[.148, .289]
	Working excessively	– .115	.039	-2.977	.003	[-.191, – .039]
	China vs. Germany	4.876	1.610	3.030	.002	[1.719, 8.034]
	The UK vs. Germany	4.025	1.235	3.259	.001	[1.602, 6.447]
	Working compulsively (China vs. Germany)	– .048	.056	– .865	.387	[-.158, .061]
	Working compulsively (The UK vs. Germany)	– .156	.047	-3.338	< .001	[-.247, – .064]
	Working excessively (China vs. Germany)	.098	.048	2.035	.042	[.003, .192]
	Working excessively (The UK vs. Germany)	.101	.051	1.998	.046	[.002, .201]
	$R^2 = 19.67\%$; $F(8, 1481) = 45.32$; $p < .001$					
Relational dependency	Intercept	14.139	1.016	13.911	< .001	[12.146, 16.133]
	Working compulsively	.194	.040	4.871	< .001	[.116, .273]
	Working excessively	– .116	.043	-2.695	.007	[-.200, – .031]
	China vs. Germany	5.651	1.784	3.168	.002	[2.152, 9.150]
	The UK vs. Germany	.717	1.369	.524	.601	[-1.968, 3.401]
	Working compulsively (China vs. Germany)	.032	.062	.524	.600	[-.089, .154]
	Working compulsively (The UK vs. Germany)	– .141	.052	-2.724	.006	[-.242, – .039]
	Working excessively (China vs. Germany)	.006	.053	.104	.917	[-.099, .110]

Dependent variable	Effect	Estimate	Std. error	t-value	p-value	95% CI
	Working excessively (The UK vs. Germany)	.044	.056	.779	.436	[-.066, .154]
$R^2 = 28.78\%$; $F(8, 1481) = 74.81$; $p < .001$						

Notably, the interaction between working compulsively and being in the UK sample was significant and negative ($\beta = -.156$, $SE = .047$, $t = -3.338$, $p < .001$), indicating that the positive relationship between working compulsively and instrumental dependency is weaker among British participants compared to German participants. This means that while individuals who tend to work compulsively generally show greater reliance on LLMs for instrumental purposes, this pattern is less pronounced among British participants. For German participants, higher levels of compulsive work behavior are more strongly linked with increased instrumental use of LLMs. However, for British participants, this relationship is attenuated, suggesting that even when British individuals showed compulsive work habits, they are less likely than Germans to increase their use of LLMs to support their work tasks.

However, the interaction between working compulsively and being a Chinese participant was not significant, indicating that the relationship between compulsive work behavior and instrumental dependency on LLMs does not differ between Chinese and German participants. In other words, for both Chinese and German individuals, the tendency to work compulsively is similarly associated with their instrumental use of LLMs.

Additionally, the interaction effects for working excessively were positive and significant for both China ($\beta = .098$, $SE = .048$, $t = 2.035$, $p = .042$) and the UK samples ($\beta = .101$, $SE = .051$, $t = 1.998$, $p = .046$). This indicates that the relationship between working excessively and instrumental dependency on LLMs is stronger among Chinese and British participants compared to the German reference group. While the main effect for working excessively was negative, these significant positive interaction terms suggest that, for Chinese and British individuals, higher levels of excessive work are linked to increased instrumental use of LLMs. In other words, in both the China and the UK samples, individuals who engage in excessive work behavior are more likely to depend on LLMs for practical, task-oriented support than their German counterparts.

The regression model for LLM relational dependency was also significant, $F(8, 1481) = 74.81$, $p < .001$, accounting for 28.78% of the variance. Similar to instrumental dependency, working compulsively was positively associated with relational dependency ($\beta = .194$, $SE = .040$, $t = 4.871$, $p < .001$). This means that individuals who exhibit higher levels of compulsive work behavior are also more likely to develop a relational attachment or dependency on LLMs. The positive association suggests that people who are driven by internal pressures to work compulsively may turn to LLMs for relational purposes. In contrast, working excessively was a negative predictor for LLM relational dependency ($\beta = -.116$, $SE = .043$, $t = -2.695$, $p = .007$). This indicates that individuals who simply spend long hours at work or are highly involved in their work activities are less likely to form relational dependencies on LLMs.

The main effect of country was positive and significant for the Chinese sample, indicating that Chinese participants reported significantly higher relational dependency on LLMs compared to their German counterparts ($\beta = 5.651$, $SE = 1.784$, $t = 3.168$, $p = .002$). In contrast, the difference in LLM relational dependency between British and German participants was not statistically significant, suggesting that British participants' levels of relational dependency were comparable to those of the German sample.

The interaction between working compulsively and being in the UK sample was significant and negative ($\beta = -.141$, $SE = .052$, $t = -2.724$, $p = .006$). This finding indicates that the positive relationship between working compulsively and relational dependency on LLMs is weaker among British participants compared to the Germany reference group. In other words, while individuals who display high levels of compulsive work behavior generally tend to develop stronger relational dependencies on LLMs, this tendency is less pronounced among British respondents. The interaction between working compulsively and being a Chinese participant was found to be non-significant. This means that the association between compulsive work behavior and relational dependency on LLMs does not differ between Chinese and German participants. In other words, individuals from both China and Germany who exhibit high levels of compulsive working tend to show similar patterns in developing relational dependency on LLMs. Additionally, none of the interaction terms between working excessively and country were significant predictors for relational dependency on LLMs. This suggests that the associations between working excessively and relational dependency on LLMs are consistent with those observed in the Germany reference group and do not vary by country. Overall, these findings highlight that the moderating role of country is specific to the relationship between working compulsively and relational dependency in the UK context.

Overall, these results indicate that working compulsively is consistently associated with greater LLM dependency for both instrumental and relational purposes, whereas working excessively predicts lower dependency. Importantly, the relationship between workaholism dimensions and LLM dependency is moderated by cultural context, particularly in the UK sample, where the effects of working compulsively are diminished.

Figure 3 depicts scatter plots illustrating the relationship between LLM dependency and workaholism, with separate regression lines shown for each sample.

5 Discussion

As large language models (LLMs) become more intuitive and widely accessible, employees are increasingly turning to them by default to support and enhance their performance across a range of work activities. In addition to streamlining workflows, LLMs are often used as a substitute for seeking advice, especially when employees encounter difficulties in the workplace (Wester et al., 2024). This is especially relevant for individuals with workaholic tendencies, who are often driven by internal and external pressures that push them to keep working. This compulsive and extreme need to work can lead

them to depend more on LLMs. The present study aimed to investigate the association between workaholism and dependency on LLMs across three samples from China, the UK, and Germany,

The results indicated that working compulsively is positively and significantly associated with instrumental dependency on LLMs across all three groups, suggesting that individuals driven by an uncontrollable urge to work are more likely to use LLMs as practical tools. This finding is consistent with prior studies that individuals with compulsive work habits struggle to detach from their work, so turning to LLMs offers them a way to continue working for longer periods (Rayat et al., 2025). We also tested, a significant association between compulsive work behavior and relational dependency on LLMs among Chinese and German participants. This finding provides insight into how compulsive work tendencies may contribute to increased dependency on LLMs, potentially as a means of refining work outputs and enhancing self-confidence in the workplace when LLMs have gradually earned the trust from users (He et al., 2025; Söllner et al., 2025). According to Mudrack (2006), compulsive workers often perceive that they accomplish less, not due to a lack of effort, but because their perfectionism compels them to pursue unattainably high standards. It is plausible that compulsive workers in both Chinese and German contexts may turn to LLMs not only as practical tools but also as relational resources. For individuals who struggle with workplace relationships due to perfectionist pressures (Schaufeli et al., 2009) and associated frustrations (Porter, 2001), LLMs may serve as a substitute for social interaction or as means to manage work-related communications in a less emotionally taxing way. By relying more on LLMs for relational purposes, compulsive workers may attempt to mitigate the stress and emotional strain that come from their high standards and social difficulties.

The pooled regression analyses provide robust evidence that the two core components of workaholism exert distinct and theoretically meaningful effects on LLM dependency across cultural contexts. Working compulsively emerged as a consistent positive predictor of both instrumental and relational dependency, which aligns with conceptualizations of compulsive work as driven by personality traits, emotional stability, satisfaction with life, internalized pressure, obsessive work-related thoughts, and difficulty disengaging from work (Schaufeli et al., 2009). Individuals who work compulsively often rely on immediate, always-accessible resources to maintain their work involvement (Schaufeli et al., 2008a), needs, LLMs promise to satisfy by providing rapid information and decision support. The finding that compulsive work patterns predict relational dependency is in line with work showing that individuals experiencing chronic strain or loneliness are more likely to anthropomorphize and emotionally rely on digital agents to meet unmet social needs (Feng & Dang, 2025; Christoforakos & Diefenbach, 2023; Li et al., 2021). In contrast, working excessively negatively predicted both types of LLM dependency. This finding extends prior research suggesting that working to excess primarily reflects behavioral overinvolvement rather than genuine psychological reliance on or emotional attachment to work. (Schaufeli et al., 2008b; Schaufeli et al., 2009; Ten Brummelhuis et al., 2017). Excessive workers may be too deeply immersed in work tasks or too bound by traditional work routines to incorporate new tools such as LLMs, which may disrupt their established workflow.

The country main effects provide further important insights. Participants from China and the UK reported substantially higher instrumental dependency compared to those from Germany, which is consistent with cultural and institutional differences in the adoption of digital technologies and AI tools. China has long been recognized for its rapid AI integration and strong societal endorsement of digital innovation (Folk et al., 2025; Wu et al., 2025), whereas the UK is one of the most Europe's most innovation-oriented and AI-positive contexts (Modhvia, & Sippy, 2025). Germany, by contrast, is known for its more cautious and regulation-oriented stance toward digital automation (Brauner et al., 2024), which may explain the comparatively lower LLM dependency. For relational dependency, only Chinese participants reported significantly higher levels than Germans. This pattern corresponds with research showing that East Asian cultures exhibit stronger relational orientations toward technology and greater willingness to treat AI as a social or quasi-social actor (Folk et al., 2025). German and British participants, in contrast, generally adopt more instrumental perspectives toward technology use.

Another reason for the higher relational dependency observed among Chinese participants may be the tendency for individuals in Chinese workplaces to be more reserved in expressing their opinions compared to many Western cultures, largely due to the cultural emphasis on group harmony and respect for organizational hierarchy. Silence is common among Chinese employees, who often choose to withhold their views and remain quiet (Yao et al., 2009). As a result, they may turn to LLMs for relational support, possibly because these tools offer a greater sense of privacy and safety than sharing concerns or questions with co-workers.

The findings also revealed cultural differences in how compulsive work behavior predicts instrumental and relational dependency on LLMs. Specifically, the effect of working compulsively on both forms of dependency is stronger among German participants compared to those from the UK sample. German individuals who exhibit compulsive work tendencies are more likely to depend on LLMs to support their work tasks and social interactions than their British counterparts. In contrast, the impact of working compulsively on both instrumental and relational dependency on LLMs did not differ significantly between German and Chinese participants. This finding points to a shared pattern in which compulsive work habits are similarly linked to increased instrumental and relational use of LLMs in both groups.

Implications

The findings of this study highlight that compulsive work behavior significantly increases dependency on LLMs. Individuals with high levels of compulsive workaholicism are often preoccupied with work-related thoughts, even outside of working hours (Schaufeli et al., 2008a). LLMs further facilitate this by providing greater opportunities to stay connected to work at any time and from any location. This reliance on LLMs may make it more difficult for compulsive workaholics to maintain clear boundaries between work and personal life, often resulting in work demands encroaching on their personal time (Aziz et al., 2010). Such continual engagement with work can negatively impact employee well-being, manifesting as lower life satisfaction (Andreassen et al., 2011), poorer health (Salanova et al., 2016; Schaufeli et al., 2008b), and heightened acute and chronic strain (Taris et al., 2005; Clark et al., 2016). Furthermore, prior studies

underscored the potential risks associated with increased reliance on AI, such as stress and burnout, as well as the pressure to align personal values with organizational goals, which can exacerbate exhaustion similar to that observed in cognitive workaholics (Santisteban et al., 2021; Rayat et al., 2025). These findings suggest that organizations should carefully consider the implementation of LLMs, ensuring that adoption strategies do not amplify negative effects on employee well-being. Managers play a crucial role in balancing technology use with the promotion of employee health and satisfaction, implementing policies that support both effective LLM integration and the common good, while mitigating risks associated with workaholic tendencies and burnout.

According to dependency theory (Venkatesh et al., 2003), the perceived usefulness and ease of use are key factors in technology adoption, qualities that are particularly strong in LLMs, which facilitate constant work engagement for time-pressed employees. This ease of access may lower the threshold for cognitive effort, as employees increasingly begin tasks with AI-generated suggestions, potentially diminishing their own engagement and decision-making responsibility (Hunkenschroer & Luetge, 2022). To address these challenges, organizations should consider strategies to maintain employee cognitive engagement while leveraging the practical benefits of LLMs. For example, expanding digital wellness initiatives to include AI ethics modules and reflective exercises (Tiwari, 2024), can promote responsible technology use. Another key approach involves introducing LLM literacy programs that extend beyond basic technical instruction to cover topics such as ethical considerations, responsible usage, and the limitations of automation. Additionally, implementing guidelines to distinguish between tasks appropriate for LLM assistance and those requiring independent human judgment can help ensure that essential leadership and analytical skills are preserved, even as dependency on LLMs grows in the workplace.

For future studies, researchers could examine user agency in the adoption and use of LLMs within professional settings. For instance, it would be valuable to investigate whether LLMs are being integrated as routine work assistants or companions, as well as how their use may contribute to increased work efficiency. Additionally, exploring the potential of LLMs to support individuals with excessive or compulsive work habits, particularly in helping them disengage from work and maintain a healthier work-life balance, would provide important insights for both theory and practice.

While our study focused on the relationship between workaholism and LLM dependency, it did not explore the potential influence of demographic factors such as age and gender. Previous research indicates that these variables may impact both workaholic tendencies and attitude toward AI; for example, younger employees may be more motivated to prove themselves and thus more likely to engage in workaholic behaviors and rely on LLMs (Ng & Feldman, 2010), whereas older employees may possess more established coping mechanisms and prioritize work-life balance, potentially lessening their reliance on such technologies. Moreover, gender and age differences can impact acceptance and comfort with technology, with males and younger adults often demonstrating higher levels of adoption (Rahman et al., 2024; Zhang et al., 2014; Czaja et al., 2006). Future research could enhance

understanding of these relationships by examining how demographic factors moderate the connection between workaholism and LLM dependency.

Limitations

One limitation of our study is that we did not examine the specific job roles of participants, which may have influenced their use of LLMs. Some individuals may have duties that do not typically require interaction with LLMs, while others may hold positions where such tools are integral to their daily tasks. Although we excluded participants who do not use LLMs from our study, a universal approach to LLMs policies may not be practical, as diversity in jobs demands distinct types and levels of cognitive engagement. Future research could extend this work by examining how different job roles or task demands shape patterns of LLM dependency. This deeper analysis would provide a more nuanced understanding of how and why people engage with LLMs in various professional contexts.

Another limitation of this study is its reliance on cross-sectional data, which prevents us from establishing causal associations between work-related factors and LLMs dependency. Given the rapid evolution of LLMs, behaviors currently labeled as overuse or addiction may eventually become standard practices for workplace efficiency. Just as email and messaging platforms transitioned from being resisted to becoming essential tools, LLMs may similarly become integral to daily work routines. To capture these shifts over time, future research should employ longitudinal approaches to provide a deeper understanding of how LLMs adoption and its impacts evolve in professional settings.

6 Conclusion

In this study, we explored how work-related attitudes influence LLM dependency across three cultural contexts: China, Germany, and the UK. First, correlation analyses showed no significant association between working excessively and instrumental dependency in any of the three national samples. However, a negative relationship between working excessively and relational dependency emerged only among Chinese participants. In contrast, working compulsively was consistently and significantly associated with instrumental dependency across three countries. The link between working compulsively and relational dependency was significant only in China and Germany. Pooled regression analysis revealed that among German participants, working excessively had a small and negative effect on both instrumental and relational dependency, while working compulsively had a positive and significant effect on both forms of dependency. Notably, the effects of working compulsively on instrumental and relational dependency were stronger in the UK sample compared to the Germany sample, but no such differences were observed between Chinese and German participants. Additionally, the impact of working excessively on instrumental dependency was significantly greater in Germany than in both the UK and China. This suggests that national context significantly moderates the relationship between compulsive work and relational dependency on LLMs. There were no significant cross-cultural differences regarding the effect of working excessively on relational dependency.

Taken together, these findings highlight distinct cultural patterns in how workaholic behaviors relate to LLM dependency. While working compulsively consistently predicts greater instrumental dependency across cultures, its association with relational dependency appears more culturally specific. Meanwhile, the influence of working excessively on LLM dependency is generally weak or negative and varies by country. Therefore, we conclude that individuals with compulsive work habits are prone to developing both instrumental and relational dependency on LLMs, which may contribute to increased burnout and reduced well-being. To address this, organizations should implement thoughtful strategies for LLMs adoption that prioritize employee well-being and help mitigate overdependence, particularly among those with compulsive workaholic tendencies.

Declarations

Conflict of interest

The authors declare no competing interests.

Ethics approval

This study was approved by the Ethics Research Committee at Bournemouth University, UK (N62239, 03.03.2025) in accordance with the 1964 Helsinki Declaration.

Consent to participate

All participants provided informed consent prior to participation.

Consent to Publish

All participants provided informed consent for publication of their data prior to participation.

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Author Contribution

- B.B.: Conceptualised the research, performed and reported the statistical analysis and wrote the original draft.- M.A.K: Conceptualised the research, validated the analysis, critically reviewed and edited the paper- A.Y.: Conceptualised and designed the study, curated the English Data, mentored and

validated the statistical analysis, and reviewed and edited the paper.- H.Y.: Designed the Chinese version of the survey, curated the Chinese data, reviewed and edited the paper.- X.W.: Contributed to the conceptualisation of the research, validated the analysis, reviewed and edited the paper.- T.Y.M.: Designed the Chinese version of the survey, curated the Chinese data, reviewed and edited the paper.- S.A.: Contributed to the conceptualisation of the research, curated the English data, and reviewed and edited the paper.- M.L.: Designed the German version of the survey, curated the German data, contributed to the original draft and reviewed and edited the paper.- R.A.: Conceptualised, designed, and mentored the research, curated the English data, reviewed and edited the paper.

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Data Availability

The datasets generated by the survey research and codes for analysis are available in the Open Science Framework repository at [https://osf.io/vcpzr/overview?view_only=8fff763e40ec4311bd64045856b28d48](https://osf.io/vcpzr/overview?view_only=8fff763e40ec4311bd64045856b28d48) . The author confirms that all data generated or analysed during this study are included in this published article.

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Figures

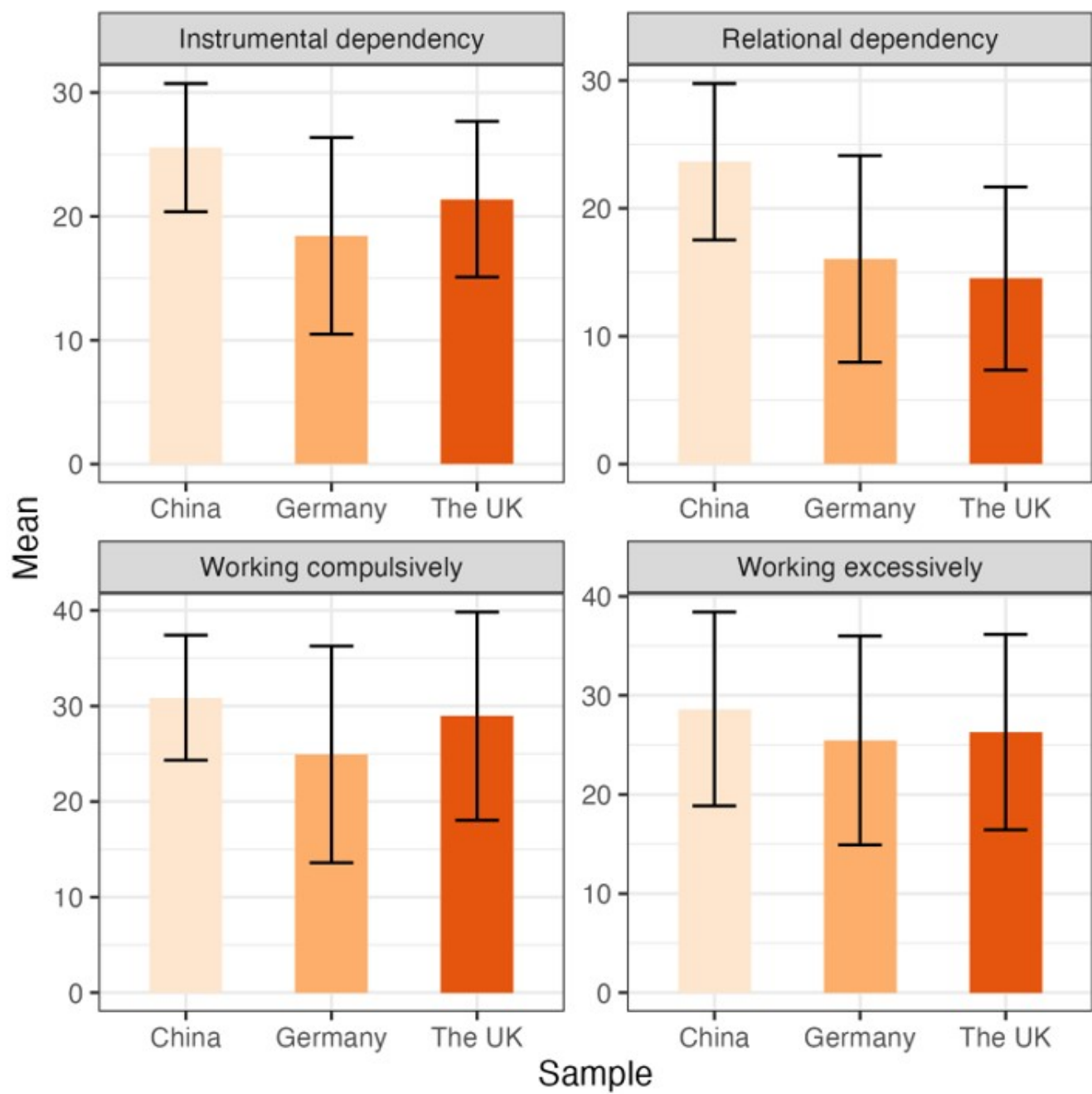


Figure 1

The bar charts of study variables across three samples with $\pm$ SD error bars.

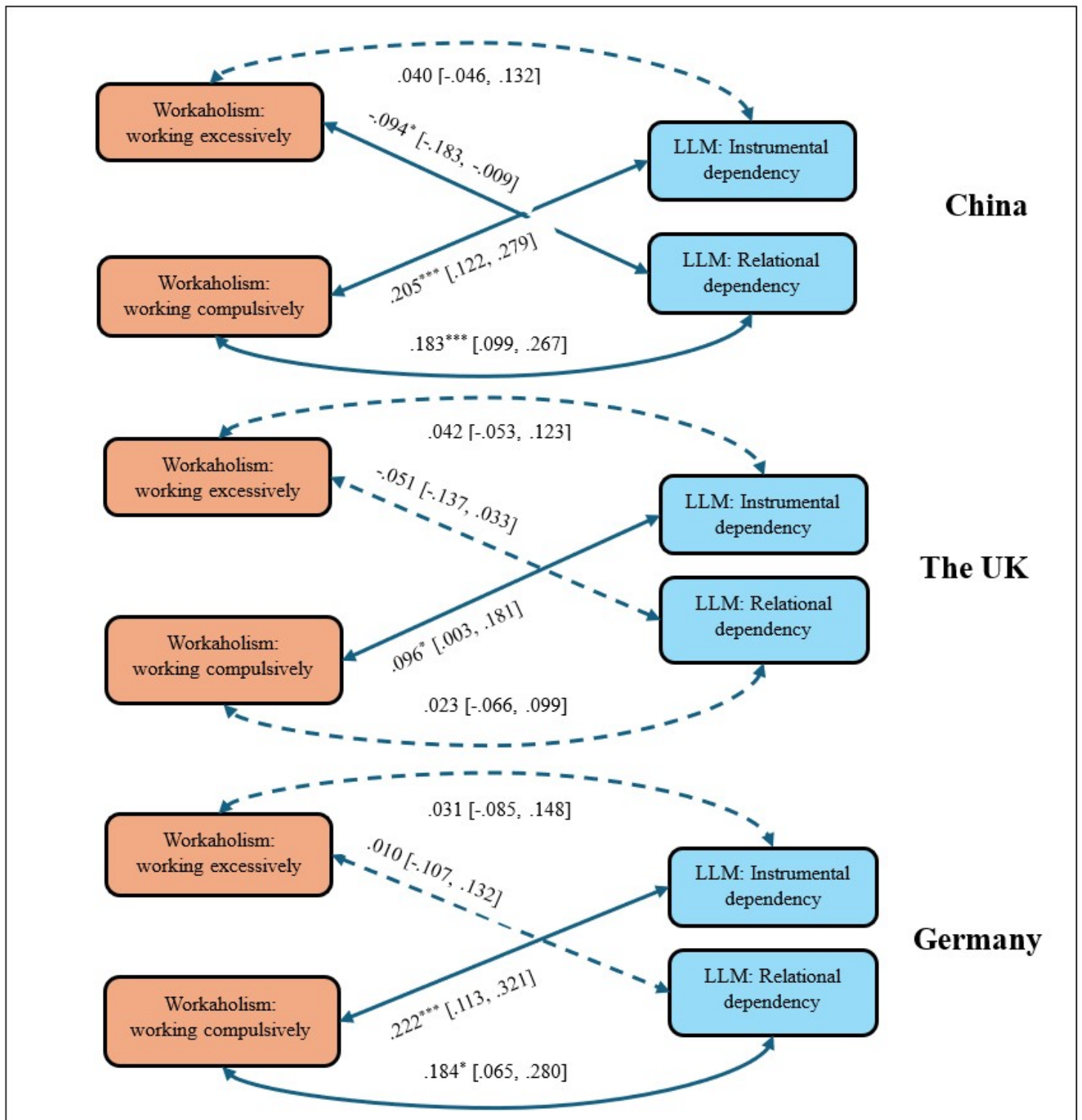


Figure 2

Diagram of correlation results of workaholism versus LLM dependency for three samples. Non-significant associations are shown with dashed lines in the figure.

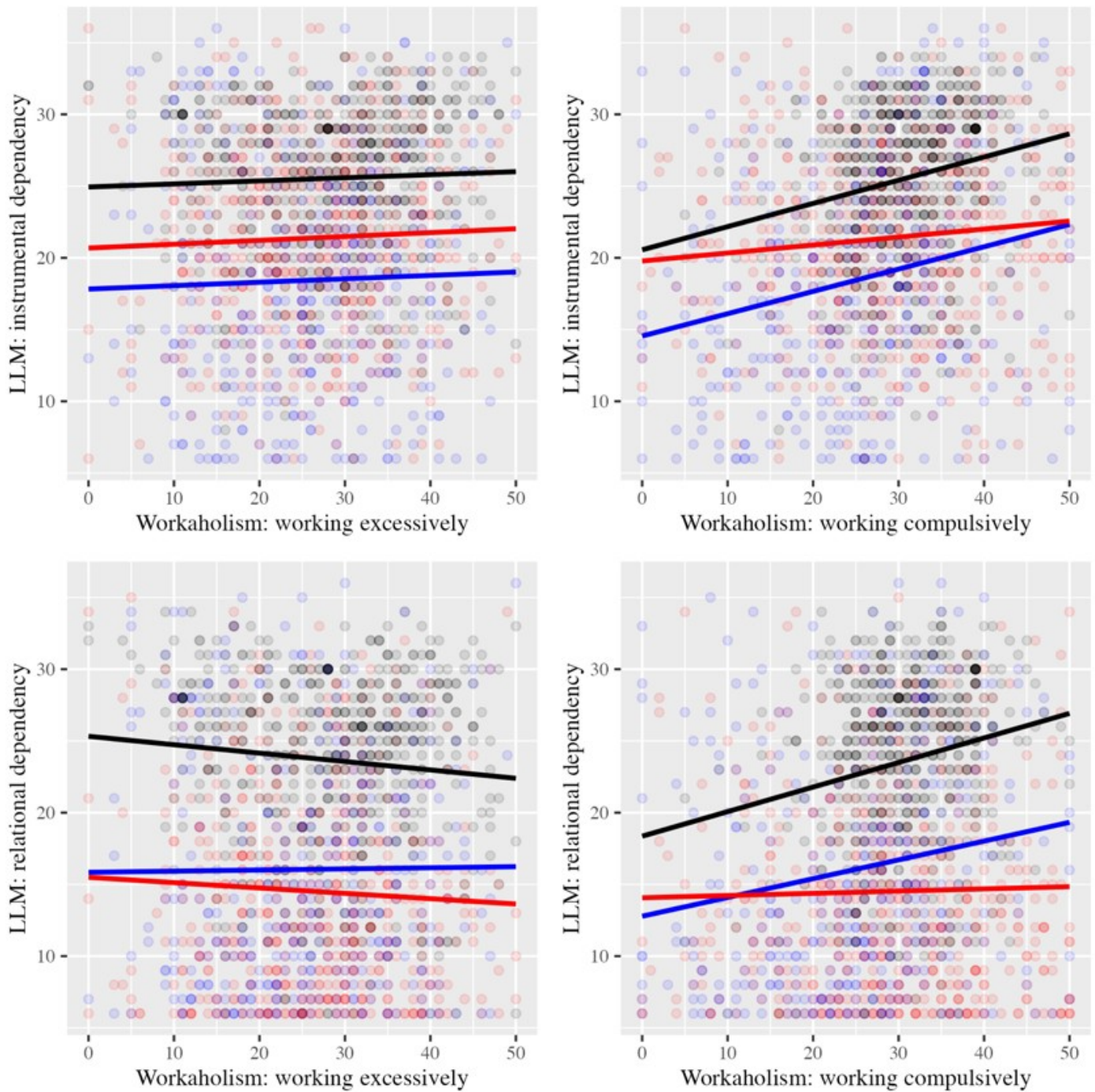


Figure 3

Scatter plots of LLM dependency vs Workaholism across samples. (Black line for China; blue line for Germany; red line for the UK).