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NEGATIVE RELATIONSHIP BETWEEN CULTURAL INDIVIDUALISM AND CHATGPT USAGE. SOCIOLOGICAL ANALYSIS ACROSS 21 COUNTRIES

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Abstract: *This study investigates the explanatory potential of cultural dimensions on ChatGPT usage rates at the societal level across 21 countries. The research uses country-level regression models (n = 21) to examine the relationship between Hofstede's cultural dimensions and ChatGPT usage reported in a late 2023 survey. Results reveal a significant negative relationship between one dimension, Individualism/Collectivism, and ChatGPT usage, with collectivist societies such as Kenya, Pakistan, and India exhibiting the highest usage rates. This suggests that generative artificial intelligence adoption in these cultures was driven by imitation rather than innovation. The paper also discusses the issues of digital and data colonialism in the Global South, where ChatGPT usage reflects both technological diffusion and economic exploitation. The study provides insights into the intersection of culture, generative artificial intelligence, and global power dynamics.*

Keywords: *ChatGPT, cross-cultural studies, generative artificial intelligence, diffusion of innovation, digital colonialism, data colonialism*

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INTRODUCTION

ChatGPT, a chatbot developed by OpenAI, has become a poster child of the ongoing generative artificial intelligence (genAI) revolution and its global diffusion (Sætra, 2023). GenAI, a subset of artificial intelligence (AI), is an umbrella term for machine learning-based systems trained on digital data to produce outputs in response to user prompts. ChatGPT is a conversational bot capable of generating coherent text outputs (Sætra, 2023). As a free and user-friendly web service (Abdaljaleel et al., 2024), the chatbot reached 100 million active users worldwide in two months since its deployment in November 2022, which was a historical record (Hu, 2023).

However, usage rates of ChatGPT vary across countries. The highest usage levels are reported in Kenya (70% of the population have already used ChatGPT) and India (66%), while French (28%) and Japanese (25%) respondents report the lowest usage of the OpenAI chatbot (Loewen et al., 2024). To uncover this disparity, this study proposes to investigate the relationship between country-level cultural factors and ChatGPT usage. These cultural factors have been proven to shape human behavioral tendencies (Lee et al., 2013) regarding information and communication technologies (ICT).

Cross-cultural Differences in AI Usage

Many attempts have been made to understand factors influencing the usage of AI (Radhakrishnan & Chattopadhyay, 2020; Tubadji et al., 2021), chatbots (Shin et al., 2022; Skjuve et al., 2019; Sohail et al., 2024), and ChatGPT (Abdaljaleel et al., 2024; Gude, 2023; Jo, 2023; Youssef et al., 2024). However, studies at the individual user level dominate the social science investigations in the field. None of nearly 4,000 studies on chatbot adoption (Alsharhan et al., 2024) employed anything beyond individual-level investigation, and none of them employed Hofstede’s (2001) cultural factors framework, which is utilized in this paper. One notable exception is Tubadij et al. (2021), who incorporated cultural factors to estimate how bounded consumers’ choices are regarding AI-driven financial services. While their work does not use Hofstede’s framework and is concerned with a narrow AI application, it provides evidence that cultural differences across 11 studied countries play a crucial role in how readily consumers adopt AI. Similarly, Shin et al. (2022) compared the United States of America and the United Arab Emirates to investigate how Hofstede’s cultural dimensions influence the perception and adoption of chatbot-driven news services. Their findings reveal that cultural values affect how users interact with and trust algorithmic news, with distinct differences observed between the two countries. Despite these contributions, the influence of cultural factors on ChatGPT adoption remains underexplored. Thus, previous studies have largely overlooked cross-cultural differences in AI usage in general, specifically of ChatGPT. This paper is intended to fill this gap.

Nevertheless, a growing body of work on socio-cultural AI differs substantially from computer science or engineering AI research (Feher & Katona, 2021; Liu, 2021). From a socio-cultural perspective, AIs are investigated and theorized as sociotechnical systems. Such systems are, on the one hand, developed, deployed, regulated, and used by humans in the culture, but on the other hand, AI systems shape the culture, and they even are the culture themselves (Elliott, 2019; Filipek, 2024; Seaver, 2017). This paper contributes to the growing field of socio-cultural AI by adopting the sociotechnical framework. However, my research approaches AI from a narrower technical AI perspective, as conceptualized by Liu (2019), which treats AI as a meta-technology and examines its various applications. I focus specifically on ChatGPT, a popular genAI application, and consider culture an explanatory variable in understanding its usage patterns.

Moreover, this paper is informed by Bass's (1969) model of the diffusion process of a product, with the effects of innovation and imitation included. This model was employed in "The Diffusion of Innovation" (Rogers, 1995), suggesting that the patterns of the ICT diffusion cycle in a community of users are shaped by communication and social influence, where later adopters are informed by earlier adopters. In the mobile phone diffusion studies, the ICT spread cycle was delineated across countries based on Hofstede's cultural dimensions (Lee et al., 2013). As Rogers (1995) defines innovation as an object, practice, or idea perceived as new by an individual or a group, ChatGPT undoubtedly represents an innovative tool (Jo, 2023).

Established technology acceptance models, such as Unified Theory of Acceptance and Use of Technology, focus on individual behavioral intention and treat contextual factors, including culture, as moderators of individual cognition (Venkatesh et al., 2003). Because this paper examines ChatGPT usage at the country level, it draws instead on Rogers' diffusion of innovations framework and Hofstede's cultural dimensions to capture culture as a structural characteristic shaping societal diffusion patterns rather than individual decisions.

Hofstede's model is a widely used cultural theory in ICT adoption research (Lee et al., 2013). In this model, culture is defined as a societal construct, a collective programming of the human mind that distinguishes members of one group from another (Hofstede, 2001). Culture manifests through values, rituals, symbols, and heroes, forming an intersubjective reference system that guides desired and undesired behaviors within a society. Although the term "culture" can apply to any collective of people, it is used to refer to societies operationalized as nations or ethnic groups. Therefore, Hofstede's model (2001) is primarily used to analyze national culture, with countries serving as a proxy in quantitative analysis. The current version of Hofstede's model includes six empirically identified dimensions that address fundamental societal issues: Power Distance, Individualism/Collectivism, Motivation Toward Achievement and Success, Uncertainty Avoidance, Long-Term vs. Short-Term Orientation, and Indulgence/Restraint (The Culture Factor, 2023). Details of these dimensions are provided in the "Methods" section.

Despite its critique, Hofstede's model is widely used for ecological, comparative multisociety studies (Hofstede, 2001). Strong evidence exists that national cultural differences, as defined and measured by this model, impact ICT adoption (Lee et al., 2013). While the validity of Hofstede's model was questioned due to its initial reliance on surveys conducted exclusively within IBM, which aimed at comparing matched samples (Goodrich & de Mooij, 2014), studies have replicated these findings across various populations (Søndergaard, 1994). Furthermore, more recent Schwartz's, Trompenaars's, and Global Leadership and Organizational Behavior Effectiveness' cultural frameworks have shown limited advancement compared to Hofstede's model (Magnusson et al., 2008). Despite Hofstede's modest stance on the constructivist nature of cultural dimensions, recent studies suggest an objective basis for these dimensions, reflected in socio-economic indicators, World Values Survey results, and geographic measures (Minkov & Kaasa, 2022).

Main Research Question and Hypotheses

The main research question in this article is: *Can cross-country differences in ChatGPT usage be explained by cultural factors?* Previous studies have provided some evidence of the relationship between four of Hofstede's dimensions – Power Distance, Individualism/Collectivism, Uncertainty Avoidance, Long-Term vs. Short-Term Orientation – and the use or adoption of ICT at the societal level (Goodrich & de Mooij, 2014; Lee et al., 2013; Shin et al., 2022). However, no similar studies exist for Motivation Towards Achievement and Success and Indulgence/Restraint. Based on suggestions from individual-level studies, I propose hypotheses at the societal level in this paper. The following six hypotheses guide the analysis:

Research suggests that societies with high Power Distance are likely to resist new technologies adoption due to reliance on hierarchical social structures and the authority of powerful members (Shin et al., 2022). *H1: There is a negative relationship between Power Distance and ChatGPT usage.*

Studies indicate that individualistic cultures are more inclined to adopt new technologies and adopt them earlier due to the enhancement of the innovation effect. In contrast, collectivist cultures are more likely to resist new technologies and adopt them later due to the enhancement of the imitation effect, as members of such societies tend to rely their decisions on group norms and social networks (Goodrich & de Mooij, 2014; Lee et al., 2013; Shin et al., 2022). *H2: There is a positive relationship between Individualism/Collectivism and ChatGPT usage.*

At the individual level, there is a growing body of work that brings evidence of the positive impact of ChatGPT usage on achievements of various kinds, especially students' academic achievement (Abdaljaleel et al., 2024; Youssef et al., 2024). While there is a lack of corresponding studies at the societal level, societies that emphasize achievement and success may likely adopt new technologies that enhance productivity and performance. *H3: There is a positive relationship between Motivation Towards Achievement and Success and ChatGPT usage.*

High Uncertainty Avoidance cultures tend to resist new and unfamiliar technologies, preferring stability and predictability (Lee et al., 2013; Shin et al., 2022). *H4: There is a negative relationship between Uncertainty Avoidance and ChatGPT usage.*

Short-Term Oriented cultures are more inclined to adopt new technologies early due to the innovation effect. In contrast, Long-Term cultures are more likely to resist and adopt them later due to the imitation effect (Lee et al., 2013). *H5: There is a negative relationship between Long-Term vs. Short-Term Orientation and ChatGPT usage.*

Ease of use combined with quick completion of laborious text-focused tasks is an advantage of ChatGPT emphasized both by research participants and researchers (Abdaljaleel et al., 2024; Youssef et al., 2024). Thus, Indulgent cultures may be more likely to embrace new technologies that reduce workload and offer more leisure time. *H6: There is a positive relationship between Indulgence/Restraint and ChatGPT usage.*

METHODS

The analysis conducted for this paper is a quantitative desk research combining country-level data from multiple sources. Unless otherwise stated, all data reflect measures or estimates for 2023.

Data regarding ChatGPT usage levels come from a global census-targeted survey study on behaviors, opinions, perceptions of, and attitudes toward artificial intelligence, entitled "Global Public Opinion on Artificial Intelligence" (GPO-AI), conducted in October and November 2023 by the University of Toronto (Loewen et al., 2024). The survey included 21 countries, the population of which represents more than half of the world's population. Respondents from Canada, Mexico, and the United States of America (USA) participated in the study in North America. In South America, included countries were Argentina, Brazil, and Chile. Europe, France, Germany, Italy, Poland, Portugal, Spain, and the United Kingdom were included. In Africa, it was Kenya and South Africa. The Asian countries included China, India, Indonesia, Japan, and Pakistan. Australia represented the global region of Oceania. At least 1,000 people in each country participated in the survey, and the total of respondents was 23,882 individuals (Loewen et al., 2024). Along with Ipsos and Pew Research Center surveys, GPO-AI was included in the Stanford AI Index (Maslej et al., 2024).

Among the three high-quality studies (GPO-AI, Ipsos, and Pew Research Center), the GPO-AI survey was chosen as the data source for this paper because it is the only one providing data on ChatGPT usage behavior. While the study's authors did not specify the sampling method, they referred to it as a "global representative survey" (Loewen et al., 2024, p. 1). The selection of countries appears to be purposeful, and while the sampling method for individuals might be random, I assume that the survey results are representative of each country's population. In contrast to the Authors, I do not aggregate results at the global level. Instead, I focus on individual countries as the unit of analysis.

For the analysis, the percentage of respondents who answered "yes" to the survey question "Have you already used ChatGPT?" was used as a measure of ChatGPT usage in the population (GPTUSE). The question was administered to all respondents without preconditions (Loewen et al., 2024). GPTUSE was treated as the dependent variable in this paper's modeling process. As shown in Table 1, GPTUSE varies from 25% in Japan to 70% in Kenya (M = 40.2, SD = 13.4). Other countries with high levels of ChatGPT usage include India (66%), Pakistan (61%), and Indonesia (59%). In contrast, GPTUSE does not exceed 50% in other countries, with the lowest levels found in France (28%), the USA, and Australia (both 29%), excluding Japan.

Population data were obtained from United Nations annual estimates (United Nations, Department of Economic and Social Affairs, Population Division, 2024). For each country, estimates for both sexes across age groups from 0 to 100+ were summed to represent the total population. These population data were used as a weighting variable in the robust model testing. Figure 1 depicts the size of populations and surveyed ChatGPT usage for 21 countries included in this analysis on a world map.

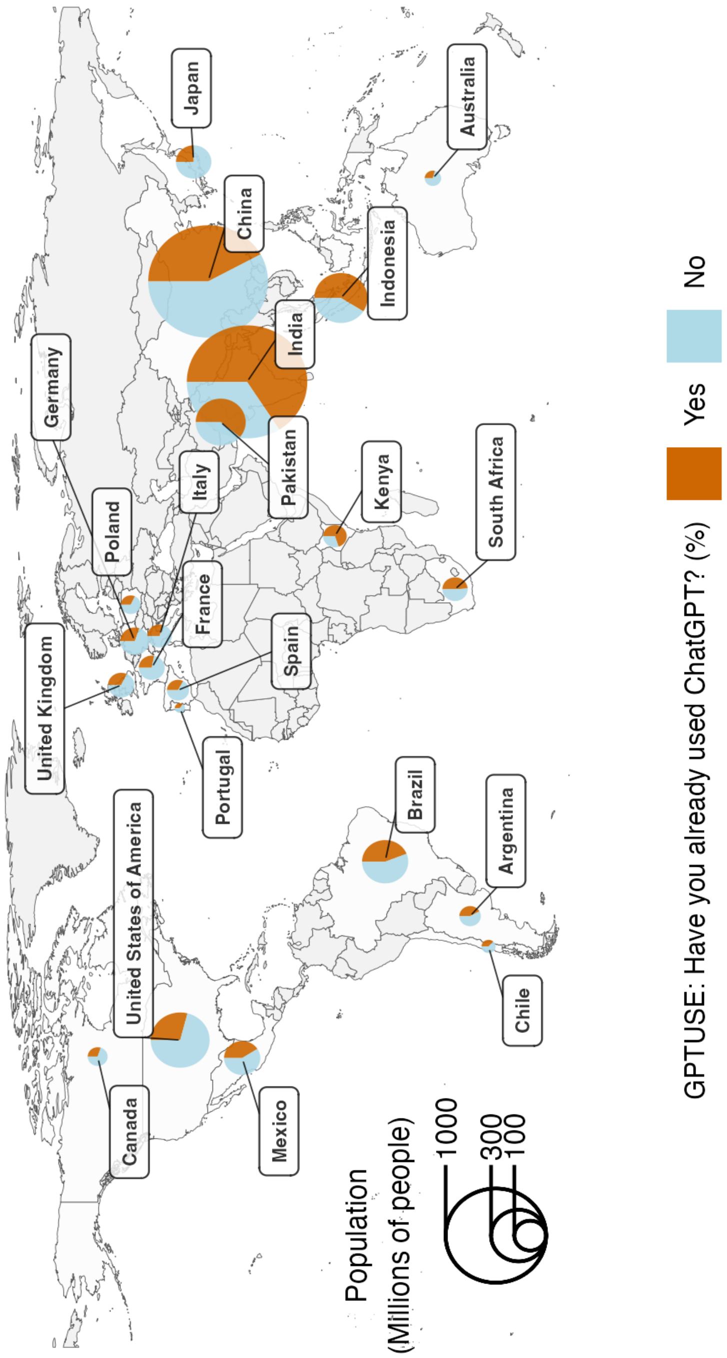

Figure 1. ChatGPT Usage Rate with Population Size of 21 Countries.

Note. GPTUSE = the percentage of respondents who answered "yes" to the survey question "Have you already used ChatGPT?" (Loewen et al., 2024), Population = estimates for both sexes across age groups from 0 to 100+, in millions of people (United Nations, Department of Economic and Social Affairs, Population Division, 2024).

Data on the most recent values of Hofstede's six cultural indexes were obtained from the country comparison tool (The Culture Factor, 2023). Quantitative applications that use culture index scores of countries as explanatory variables are typical for comparing ten or more countries (Hofstede, 2001).

Power Distance (PDI) reflects the extent to which the less powerful members of institutions and organizations accept unequal power distribution. Thus, it measures the endorsement of inequality from below. Low PDI societies tend to have student-centered education and rare political corruption, while large PDI tend to have teacher-centered education and more frequent corruption (Hofstede, 2011).

Individualism/Collectivism (IND) measures how society members maintain independence versus integration into groups. High IND characterizes individualistic societies, where "I" consciousness prevails, tasks take priority over relationships, and members are expected to care for themselves and their immediate family. However, individualistic societies emphasize the protection of personal freedoms and rights. In contrast, low IND denotes collectivist societies, where "We" consciousness prevails, relationships take precedence over tasks, and members live in extended families or clans, caring for each other in exchange for loyalty. Collectivism tends to prioritize group rights, impose strict, normative rules of behavior, and suppress deviations from these norms (Hofstede, 2011; Minkov & Kaasa, 2022).

Motivation Towards Achievement and Success (ASU), previously known as the Masculinity/Femininity index, measures values related to competition, achievement, and quality of life. A high ASU indicates a "decisive" society driven by competition, where success is defined by being the best in one's field. This pole values competitiveness, assertiveness, and strength. Conversely, a low ASU signifies a "consensus-oriented" society where the quality of life is the measure of success. Low ASU characterizes a culture of work-life balance, sympathy for the weak members, modesty, and gender equality (Hofstede, 2011; The Culture Factor, 2023).

Uncertainty Avoidance (UAI) indicates the level of ambiguity tolerance in society. Thus, it measures to what extent a culture minimizes the possibility of unstructured, chaotic situations. Weak UAI signals a society where chaos is an immanent part of everyday life, teachers may not know all the answers, and deviant persons and ideas are curious. Strong UAI characterizes a society where chaos is a threat that must be controlled, teachers are expected to know all the answers, and deviances are dangerous (Hofstede, 2011).

Long-Term vs. Short-Term Orientation (LTO) measures how much a culture values future rewards versus immediate outcomes. Long-term-oriented cultures score high on LTO and are characterized by persistence and thrift. These societies tend to adapt pragmatically to changing circumstances and emphasize the future. In contrast, short-term oriented cultures score low on LTO. Such cultures value immediate outcomes and the preservation of established norms and traditions, emphasizing the present and the past (Hofstede, 2001, 2011).

Indulgence/Restraint (IUG) reflects how impulses and desires are restrained in a society. Indulgence is represented by high scores on IUG and stands for the value of leisure, enjoying life, and having fun. Low scores on the index characterize restrained cultures, where society values control and regulation of the gratification of desires (Hofstede, 2011).

The percentage of individuals using the Internet in the population (NETUSE) stems from official data, imputation, national statistics office estimates, modeling results, analogies with nearby countries, and other sources combined by the International Telecommunication Union (World Bank Open Data, 2024). Available data for 9 of 21 analyzed countries do not cover 2023 or newer years. The newest available NETUSE for Australia, Canada, United Kingdom, Japan, Kenya, Pakistan, USA, and South Africa were 2022, and for India 2020. NETUSE was employed as a control variable in this paper because the usage of ChatGPT, a web service, depends on Internet access. By controlling for NETUSE, the effect of cultural factors on ChatGPT usage was isolated, ensuring the results reflect cultural differences rather than Internet accessibility. Descriptive statistics for all variables are included in Table 1.

Table 1. Descriptive statistics for variables used in the analysis (n = 21 countries)

Variable	M (SD)	Median [Min, Max]
GPTUSE	40.2 (13.4)	35.0 [Japan = 25.0, Kenya = 70.0]
NETUSE	80.4 (18.8)	86.4 [Pakistan = 32.9, USA = 97.1]
PDI	58.0 (15.3)	57.0 [Germany = 35.0, Mexico = 81.0]
IND	47.4 (24.2)	51.0 [Kenya = 4.0, Germany = 79.0]
ASU	56.9 (14.7)	60.0 [Chile = 28.0, Japan = 95.0]
UAI	66.3 (21.6)	70.0 [China = 30.0, Portugal = 99.0]
LTO	43.4 (22.2)	47.0 [Kenya = 11.0, Japan = 100]
IUG	49.0 (22.5)	46.0 [Pakistan = 0, Mexico = 97.0]
Population (mil)	229.7 (409.5)	66.4 [Portugal = 10.4, India = 1438.1]

Note. Descriptive statistics for the variables, including M = mean, SD = standard deviation, median, and the minimum and maximum values by country. All variables range from 0 to 100, except Population. Data for the IUG index for one country (Kenya) is missing. GPTUSE = the percentage of respondents who answered “yes” to the survey question “Have you already used ChatGPT?” (Loewen et al., 2024); NETUSE = the percentage of individuals using the Internet in the population (World Bank Open Data, 2024); PDI = Power Distance, IND = Individualism/Collectivism, ASU = Motivation Towards Achievement and Success, UAI = Uncertainty Avoidance, LTO = Long-Term vs. Short-Term Orientation, IUG = Indulgence/Restraint (The Culture Factor, 2023); Population = summed estimates across age groups from 0 to 100+, in millions of people (United Nations, Department of Economic and Social Affairs, Population Division, 2024).

The variables used in the analysis all range from 0 to 100, enabling direct comparison of unstandardized regression coefficients and enhancing interpretability. While GPTUSE and NETUSE represent percentages within national populations and can be directly interpreted as such, the cultural dimension scores do not have meaning on their own. Instead, these indices are intended solely for between-country comparisons, and their absolute values should not be interpreted in isolation (Hofstede, 2001).

As is widely recognized in the social sciences, aggregating individual-level traits or behaviors to the country level and then drawing comparisons solely at this aggregated level can lead to the ecological fallacy. This fallacy involves mistakenly assuming that what researchers learn about the aggregated unit of analysis provides knowledge about the individuals that comprise this unit (Hofstede, 2001). In this article, the ecological fallacy does not apply, as all variables, analyses, and interpretations are conducted exclusively at the country level.

National culture shapes tendencies in individual behaviors, including behaviors related to the use of ICT. The approach adopted in this article enables the identification of ChatGPT usage patterns across cultures. Culture, understood as a system of desirable and undesirable behavior patterns, influences individual behavioral tendencies, which are reflected in population-level measures. Therefore, I assume that country-level indicators reflect these culturally shaped behavioral tendencies and allow for a meaningful cross-national comparison.

Ordinary least squares (OLS) multiple linear regression modeling was used for the analysis. Despite the limited sample size (n = 21), the application of OLS multiple regression is considered suitable for exploratory cross-national research provided that the model's assumptions are met and the number of predictors remains small (Achen, 1982). All analyses were conducted using GNU R (R Core Team, 2025). The complete data and R scripts required to reproduce the results of this study are available upon request.

RESULTS

Two model-fitting steps were employed to answer the main research question and test hypotheses. The first step aimed to estimate the relationships between GPTUSE and cultural variables, while the second step controlled for the stability and robustness of these relationships. GPTUSE was the dependent variable in all models.

In the first step, three OLS regression models were fitted (see Table 2). The baseline model (M1) included all six cultural Hofstede's dimensions as independent variables. IND coefficient was negative and statistically significant (b = -0.43, 95% CI [-0.74, -0.12], p = .010), suggesting that a higher level of individualism is associated with a lower percentage of ChatGPT users at the country level. Conversely, a lower level of individualism corresponds to higher ChatGPT usage. All other five cultural variables were non-significant, although ASU and UAI showed relatively stronger negative estimates than the remaining coefficients. M1 was fitted for 20 countries, excluding Kenya, as the IUG value was unavailable for that country (see Table 1). Tests to see if the data met the assumption of collinearity indicated that multicollinearity was not a concern in M1 (PDI, Tolerance = .33, VIF = 3.01; IND, Tolerance = .13, VIF = 7.42; ASU, Tolerance = .35, VIF = 2.88; UAI, Tolerance = .61, VIF = 1.63; LTO, Tolerance = .15, VIF = 6.56; IUG, Tolerance = .44, VIF = 2.27).

The reduced model (M2) tested the dependent variable against five cultural dimensions, excluding IUG. This reduction was motivated by the lack of a strong relationship between IUG and the dependent variable in M1 and utilization of the full dataset of 21 countries. The results of M2 did not change the relationships identified in M1. IND remained significantly negatively related to GPTUSE (b = -0.50, 95% CI [-0.72, -0.27], p <.001), while ASU and UAI remained non-significant, despite showing relatively strong negative coefficients. PDI's low coefficient and lack of statistical significance again suggest no strong relationship between this dimension and GPTUSE.

The third model was fitted to estimate how the core cultural variables performed (M3). In M3, only IND, ASU, and UAI were included. The negative relationship between IND and GPTUSE was confirmed in this model, with the estimate similar to that in M2 and narrower confidence intervals. Another predictor, UAI, became significant (b = -0.14, 95% CI [-0.25, -0.02], p = .024), suggesting that higher uncertainty avoidance is associated with lower GPT usage and vice versa. Despite a similar estimate to UAI, ASU was not statistically significant at the 5% level.

Table 2. Ordinary Least Squares Regression Analysis: Identifying Core Predictors Among Six Hofstede's Cultural Dimensions

	Dependent variable: GPTUSE								
	M1 Baseline			M2 Reduced			M3 Core		
Predictor	*Estimate*	*95% CI LL – UL*	*p*	*Estimate*	*95% CI LL – UL*	*p*	*Estimate*	*95% CI LL – UL*	*p*
Intercept	79.30	54.42 – 104.18	**<.001**	81.19	56.03 – 106.35	**<.001**	79.72	66.21 – 93.24	**<.001**
PDI	0.00	-0.28 – 0.29	.984	-0.02	-0.28 – 0.25	.904			
IND	-0.43	-0.74 – -0.12	**.010**	-0.50	-0.72 – -0.27	**<.001**	-0.47	-0.58 – -0.37	**<.001**
ASU	-0.16	-0.44 – 0.13	.253	-0.16	-0.40 – 0.08	.174	-0.14	-0.31 – 0.03	.093
UAI	-0.13	-0.28 – 0.02	.080	-0.13	-0.27 – 0.01	.061	-0.14	-0.25 – -0.02	**.024**
LTO	0.01	-0.29 – 0.32	.932	0.03	-0.19 – 0.24	.783			
IUG	-0.05	-0.22 – 0.13	.575						
n	20			21			21		
R^2 / adj.	.872 / .812			.880 / .840			.879 / .858		

Note. CI = confidence interval; LL = lower limit; UL = upper limit; adj. = adjusted R^2. GPTUSE = the percentage of respondents who answered "yes" to the survey question "Have you already used ChatGPT?" (Loewen et al., 2024); PDI = Power Distance, IND = Individualism/Collectivism, ASU = Motivation Towards Achievement and Success, UAI = Uncertainty Avoidance, LTO = Long-Term vs. Short-Term Orientation, IUG = Indulgence/Restraint (The Culture Factor, 2023); *n* = 20 in the Baseline model M1 due to missing data for the IUG index in one country (Kenya); $p < .05$ are in bold.

Three cultural dimensions, IND, ASU, and UAI, were identified as core predictors for GPTUSE in the first step of model fitting and were used in the second step to test the stability and robustness of the relationships (Table 3). The fourth model (M4) introduced a control variable indicating a percentage of country's population Internet users (NETUSE). Overall, including NETUSE did not alter the relationships observed in M3. However, ASU became statistically significant (b = -0.16, 95% CI [-0.28, -0.03] p = .016), indicating a negative association between Motivation Towards Achievement and Success cultural dimension and usage of ChatGPT. The negative coefficient for IND weakened in M4 compared to M3 (from b = -0.47, 95% CI [-0.58, -0.37] to b = -0.27, 95% CI [-0.41, -0.14]). The estimate for NETUSE (b = -0.32, 95% CI [-0.49, -0.14], p = .001) indicated a negative association between Internet and ChatGPT usage at the country level, which is counterintuitive. Moreover, in M4, the NETUSE estimate was stronger than for IND (b = -0.27, 95% CI [-0.41, -0.14], p = .001), which had been the strongest predictor in all three models of the first step. Illogically, there were three countries where the percentage of ChatGPT users was higher than that of Internet users: Kenya (GPTUSE 70%, NETUSE 40.8%), Pakistan (61%, 32.9%), and India (66%, 43.4%). That issue is addressed by the sixth model.

Additionally, to account for the size of each country's population, a fifth model (M5) was fitted. In this model, the four independent variables from M4 were retained, and population size was introduced as a weighting variable. The rationale behind this approach was to examine whether treating countries as unequal units based on population size (as shown in Table 1) would alter the estimated relationships. In summary, the direction of the associations remained unchanged, but some predictors' estimates were modified. Notably, ASU became the strongest predictor among Hofstede's dimensions (b = -0.23, 95% CI [-0.43, -0.03], p = .029), whereas IND had been the strongest predictor in all previous models (from M1 to M4).

The sixth model (M6) was fitted with the exact specifications as M5 but excluded four countries – Kenya, Pakistan, India, and China – to assess the robustness of the relationships. Three countries (Kenya, Pakistan, and India) have a higher percentage of ChatGPT users than Internet users. Moreover, Cook's distances in M5 for three countries are above the threshold of 1, suggesting that these countries are influential cases for the model – India (Cook's distance = 8.25), Pakistan (1.20), and China (1.94). The population weighting drove these high values in M5, leading to the decision to exclude these four countries in M6 while retaining population as the model weight and NETUSE as the control variable. Results from M6 support the previous findings, confirming a negative relationship between GPTUSE and IND (b = -0.23, 95% CI [-0.40, -0.07], p = .011). ASU exhibited similar effects as in M5, while UAI became a non-significant predictor. Final tests regarding the assumption of collinearity indicated that multicollinearity again was not a concern in M6 (IND, Tolerance = .25, *VIF* = 3.93; ASU, Tolerance = .88, *VIF* = 1.14; UAI, Tolerance = .94, *VIF* = 1.06; NETUSE, Tolerance = .25, *VIF* = 3.92). Nevertheless, IND and NETUSE were strongly positively correlated, $r(19) = .83$, $p < .001$, which is interpreted in the "Discussion".

Table 3. Ordinary Least Squares Regression Analysis: Stability and Robustness Testing

	Dependent variable: GPTUSE								
	M4 Control			**M5 Weighted**			**M6 Robust**		
Predictor	*Estimate*	*95% CI LL – UL*	*p*	*Estimate*	*95% CI LL – UL*	*p*	*Estimate*	*95% CI LL – UL*	*p*
(Intercept)	95.16	82.03 – 108.28	**<.001**	105.04	91.96 – 118.11	**<.001**	104.68	73.81 – 135.55	**<.001**
IND	-0.27	-0.41 – -0.14	**.001**	-0.18	-0.34 – -0.03	**.025**	-0.23	-0.40 – -0.07	**.011**
ASU	-0.16	-0.28 – -0.03	**.016**	-0.23	-0.43 – -0.03	**.029**	-0.20	-0.32 – -0.08	**.004**
UAI	-0.11	-0.20 – -0.03	**.014**	-0.10	-0.19 – -0.01	**.039**	-0.07	-0.16 – 0.02	.119
NETUSE	-0.32	-0.49 – -0.14	**.001**	-0.46	-0.59 – -0.32	**<.001**	-0.46	-0.85 – -0.07	**.024**
N	21			21			17		
R^2 / adj.	.938 / .922			.952 / .939			.956 / .941		

Note. CI = confidence interval; LL = lower limit; UL = upper limit; adj. = adjusted R^2. GPTUSE = the percentage of respondents who answered "yes" to the survey question "Have you already used ChatGPT?" (Loewen et al., 2024); NETUSE = the percentage of individuals using the Internet in the population (World Bank Open Data, 2024); PDI = Power Distance, IND = Individualism/Collectivism, ASU = Motivation Towards Achievement and Success, UAI = Uncertainty Avoidance, LTO = Long-Term vs. Short-Term Orientation, IUG = Indulgence/Restraint (The Culture Factor, 2023); in the Weighted Model M5 and the Robust Model M6 a weighting variable Population = summed estimates across age groups from 0 to 100+, in millions of people

(United Nations, Department of Economic and Social Affairs, Population Division, 2024) was included; $n = 17$ in the Robust model M6 due to the exclusion of Kenya, Pakistan, India, and China; $p < .05$ are in bold.

Despite the small sample size, the results are justified based on the models' fit and effect sizes. The R^2 values across the six regression models range from .872, 95% CI [.802, .942] in M1 to .956, 95% CI [.926, .986] in M6, indicating that a high proportion of variance in GPTUSE was explained by the predictors. The consistency of these values across different models further supports the robustness of the findings. Moreover, the effect sizes range from $f^2 = 6.81$ (M1) to 21.73 (M6), both exceeding the 0.35 threshold for a large effect size (Cohen, 1988).

The results of the OLS models provide mixed support for the hypotheses regarding the influence of cultural factors on ChatGPT usage across countries.

H1, which posited a negative relationship between Power Distance and ChatGPT usage, was not supported. PDI was not a significant predictor in any model (M1, M2).

H2, which suggested a positive relationship between Individualism/Collectivism and ChatGPT usage, was also not supported; instead, contrary to the hypothesis, a significant negative relationship was found across all models (M1, M2, M3, M4, M5, and M6). This indicates that individualistic cultures are associated with lower ChatGPT usage, while collectivistic cultures are associated with higher usage. This stable and robust relationship was confirmed across all six model configurations. Thus, a negative relationship between cultural individualism and ChatGPT usage is the most striking result of the analysis.

H3, proposing a positive relationship between Motivation Towards Achievement and Success and ChatGPT, was again not supported, as ASU was not a statistically significant variable in the initial models (M1, M2, M3). However, the relationship became significant in models that included control variable NETUSE (M4, M5, M6) and population weighting (M5, M6), but in a negative direction.

H4, which assumed a negative relationship between Uncertainty Avoidance and ChatGPT usage, was partially supported, with a significant negative relationship found in some models (M3, M4, and M5), though not consistent across all. Thus, the association is not robust.

H5, suggesting a negative relationship between Long-Term vs. Short-Term Orientation and ChatGPT usage, was not supported. LTO was not significant in any model (M1, M2) and was dropped from M3.

Finally, H6 was not supported, proposing a positive relationship between Indulgence/Restrain and ChatGPT usage. IUG was not a significant predictor in M1 and was dropped at this model-fitting phase.

Overall, the findings suggest that while some cultural factors, such as Motivation Towards Achievement and Success, Uncertainty Avoidance, and especially Individualism/Collectivism, do influence ChatGPT usage at the societal level, relationships in the expected direction are rare.

DISCUSSION

The primary research question of this study was whether cultural factors can explain cross-country differences in ChatGPT usage. To address this, the study aimed to explore the relationship between six Hofstede's cultural dimensions – Power Distance, Individualism/Collectivism, Motivation Towards Achievement and Success, Uncertainty Avoidance, Long-Term vs. Short-Term Orientation, and Indulgence/Restraint – and the usage of ChatGPT across 21 countries. The findings support an affirmative answer to the research question.

Cultural Individualism and the Usage of ChatGPT

This study identified a negative correlation between Individualism/Collectivism and ChatGPT usage. This relationship was the only one confirmed across six different model configurations, making it stable and robust. Contrary to the initial hypothesis, which suggested a positive relationship between Individualism/Collectivism and ChatGPT usage (H2), the hypothesis was rejected. Additionally, results indicate a negative relationship between ChatGPT usage and two other cultural factors: Motivation Towards Achievement and Success, and Uncertainty Avoidance. Nevertheless, the associations are not robust.

The key results indicate that lower levels of cultural Individualism (i.e., higher Collectivism) are associated with higher self-reported ChatGPT usage, as observed in Kenya, Pakistan, India, Indonesia, and South Africa. In these collectivist cultures, the emphasis on group norms and social networks may promote higher usage rates through collective behaviors and recommendations. Consistent with prior research (Lee et al., 2013), high reported usage in these societies appears to reflect technology infusion through imitation rather than early-stage innovation. These countries may focus on adopting and diffusing technologies developed in more advanced economies, as described in the World Development Report (World Bank, 2024). Conversely, higher levels of Individualism are associated with lower adoption rates, as seen in Germany, the United Kingdom, France, Australia, Canada, Spain, Japan, and the United States.

The observed negative relationship persists even after controlling for internet usage rates and population size and removing influential cases, suggesting that the cultural dimension of Individualism/Collectivism plays an independent role in shaping ChatGPT usage patterns at the societal level. The observed pattern indicates that at the time of the Toronto team's survey – approximately twelve months after ChatGPT's launch (Loewen et al., 2024) – the diffusion process had entered a later phase, where imitation factors outweighed innovation factors (Lee et al., 2013). While innovation factors such as perceived usefulness and ease of use drive faster adoption in high-Individualism societies at the early stages, once adoption reaches a critical mass (around 20% of the population), imitation factors such as word of mouth and subjective norms become more influential in low-Individualism societies (Goodrich & de Mooij, 2014; Lee et al., 2013; Shin et al., 2022). After considering the roles of innovation and imitation mechanisms, the results are consistent with previous studies on cultural factors in ICT diffusion.

Digital and Data Colonialism

Moreover, Individualism/Collectivism aligns with absolute geographical latitude (i.e., distance from the Equator). It distinguishes the wealthiest societies, at the individualist extreme, from the poorest ones, at the collectivist extreme (Minkov & Kaasa, 2022). Thus, the Individualism/Collectivism dimension roughly resembles the concept of the Global North and South division (Lees, 2021). In the Global South countries, ChatGPT may be used or declared to be used to imitate the behaviors of reference groups from the Global North. This suggests that ChatGPT could be seen not only as a deployment of an innovative tool but also as a web service that has achieved marketing success, especially in the Global South. This success opens the discussion regarding the incomplete decolonization of Southern minds (Adams, 2021). Populations in the Global South may use ChatGPT at higher rates because they adhere to hegemonic, colonial value systems, making them more susceptible to the promises of OpenAI for a richer, more efficient, less labor-intensive, and generally better AI-driven future.

Recent evidence on generative AI adoption supports that interpretation. Reports indicate that adoption of generative AI, and ChatGPT in particular, has been disproportionately high in middle-income and emerging economies. Middle-income countries account for more than half of global generative-AI traffic, despite their smaller economic share, while low-income countries remain marginal contributors (Liu & Wang, 2024). Users in India, Nigeria, the United Arab Emirates, Egypt, and other emerging economies report substantially higher levels of regular use of AI services than users in advanced economies (Gillespie et al., 2025). Internal OpenAI longitudinal chatbot usage data similarly indicate that the most rapid growth in ChatGPT use occurred in low- to middle-income countries with GDP per capita between $10,000 and $40,000 (Chatterji et al., 2025). These patterns mirror the results presented in this study and support the interpretation of ChatGPT diffusion as a socially driven process marked by imitation and aspirational alignment.

Interestingly, this theoretical framing is supported by empirical Internet and ChatGPT usage patterns obtained in the paper. In three countries with the highest reported usage of ChatGPT (Kenya, Pakistan, and India), the general Internet usage rate is lower than ChatGPT usage itself, suggesting possible device sharing or overreporting due to social desirability bias. Moreover, Internet usage at the country level is negatively correlated with ChatGPT usage rate and positively with Individualism/Collectivism, further suggesting its role as a proxy for the Global North and South divide, similar to the distance from the Equator indicated by Minkov and Kaasa (2022).

Additionally, the exploitation of Kenyan workers by OpenAI, who were paid less than $2 per hour for data labeling to reduce ChatGPT’s toxicity (Perrigo, 2023), exemplifies the dynamics of digital colonialism, understood as perpetuating traditional colonial practices via current technologies (Mann & Daly, 2019). Such low-wage work for various AI-related companies is well-documented in the Global South (Gray Widder et al., 2023; Irani, 2016). This situation highlights how labor from less developed countries is used to support technological advancements in the Global North, often under exploitative conditions. However, data labelers may also advocate for the use of the chatbots they train. The notion of data colonialism, defined as a new form of colonialism that combines the extractive practices of its historical predecessors with computing methods, normalizing the exploitation of humans through data (Couldry & Mejias, 2019), is also present. High levels of ChatGPT usage mean high amounts of users' data collected and reused for the profit of the web service provider (Sebastian, 2023). Within the data colonialism framework, the spread of ChatGPT represents a maturing form of capitalism that emerged from earlier big data appropriations. Unlike territorial colonialism, it operates externally and internally – both on Global South users and domestic populations (Couldry & Mejias, 2019). Moreover, this spread may not merely reflect another form of maturing capitalism but the formation of Big Tech's feudal power (Kotkin, 2020; Varoufakis, 2024), to which OpenAI contributes as a Microsoft partner (Gray Widder et al., 2023).

Limitations, Methodological Reflections, and Future Research

Several limitations should be considered. The study's reliance on self-reported data may introduce a social desirability bias, where respondents overreport their usage of ChatGPT to align with perceived social norms (DeMaio, 1984). The survey question "Have you already used ChatGPT?" may trigger fear of missing out, leading respondents, especially in the Global South countries, to overreport usage to align with perceived norms and give a favorable picture of themselves (DeMaio, 1984), particularly since the survey was administered by a Canadian university (Loewen et al., 2024). Moreover, the positive answer may indicate one-time use or experimentation with ChatGPT rather than regular usage or stable tool adoption. On the other hand, the cross-sectional nature of the survey data limits the ability to infer causality between cultural dimensions and ChatGPT usage. Possible survey data quality issues and sample biases may also play a crucial role in the observed phenomena, especially in countries with the highest percentages of ChatGPT usage. Due to the purposeful sample of 21 countries included in the survey, generalizations regarding differences between Global South and North should be taken as suggestions for further research, not strong evidence. Within the studied sample, among countries typically classified as part of the Global South, only Pakistan can be considered a low-income country, as it is the only country in the sample to rank low on the Human Development Index (HDI). Kenya and India fall into the medium HDI rank category, while the remaining countries in the sample score high or very high (United Nations Development Programme, 2025). Furthermore, the analysis does not account for demographic differences between countries. Global South countries with high ChatGPT usage tend to have younger demographics than Global North of lower usage rates (World Bank, 2024, pp. 70–71 box 3.1. *Graying growth*), and younger cohorts are more inclined to use the OpenAI's web service (Babu et al., 2024). Lastly, the paper does not consider country differences in the local chatbot market. For instance, China has many AI chatbot services aimed at its users (Tian et al., 2024), and access to ChatGPT is restricted (Bao et al., 2025), while in Italy, ChatGPT was temporarily banned (Bertomeu et al., 2025).

Future research should further explore the impact of cultural dimensions on ChatGPT and other genAI or AI services usage and investigate the intertwined phenomenon of digital and data colonialism. More research is highly needed in countries that score medium and low on the HDI rank. Researchers using Hofstede's dimensions in such inquiries are encouraged to investigate the factors wherein my study did not produce stable and robust outcomes, namely Motivation Towards Achievement and Success, and Uncertainty Avoidance, in addition to other dimensions that exhibited non-significant results. To enhance the validity of new findings, future studies should incorporate longitudinal designs to track changes in AI adoption over time, which would identify evolving patterns. A mixed-methods approach, combining qualitative insights with quantitative data, would provide a deeper understanding of how cultural factors shape attitudes and behaviors related to AI usage. Triangulating survey data with other data sources, such as usage metrics from AI web platforms and macro socioeconomic indicators, would help validate self-reported usage and reduce biases, such as social desirability bias. Improving survey design by carefully wording questions and minimizing self-report biases would further ensure more accurate data collection. Understanding the broader implications of technology adoption in different cultural contexts can provide valuable insights for technology developers, activists, and policymakers.

This study highlights the importance of cultural factors in understanding technology usage patterns across different countries. The findings suggest that cultural dimensions play a role in shaping how new technologies, such as ChatGPT, are used. Furthermore, cultural dimensions often reflect other societal and economic divisions, which enables further understanding of generative AI usage at the macro level.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

With its large and young populations, the Global South emerges as a receptive market for generative AI services, especially in collectivist societies. Competitive advantage in these regions may depend not only on economic factors but also on cultural alignment. However, the global expansion of AI raises concerns regarding data extraction practices and low-pay jobs exploiting the South in favor of the North, reinforcing the digital and data colonialism framework.

These findings also have implications for policymakers. In collectivist societies, AI strategies should leverage social influence and prepare for diffusion acceleration, while in individualistic societies, they should instead emphasize autonomy, utility, and privacy. Consistent with the notion of pro-innovation bias (Rogers, 1995), policymakers should refrain from depicting AI as inherently beneficial solely due to its innovative nature and should instead advocate for informed, critical decision-making to address the concentration of power within the global technology sector.

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