

Dual Drivers of Emotional and Efficiency Needs: A Study of Group Differences in AI Chat Dependency Behavior

Mingzhen Liu

School of Literature and media, Chengdu Jincheng College, Chengdu, 610000, China

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Abstract: Users increasingly perceive AI chatbots not merely as functional tools but as emotional companions. This study proposes a 'demand-behavior' dual-path model to examine the formation mechanisms and group heterogeneity of AI chatbot dependence, revealing how emotional compensation and efficiency enhancement synergistically operate, while identifying behavioral variation causes through cross-group analysis. This study mainly employed a questionnaire survey to collect data on user interactions with AI chatbots, analyzing motivations, engagement frequency, and contextual usage patterns. The study found that, first, emotional and efficiency needs were the primary drivers of user reliance on AI chatbots; second, AI chatbots boosted work efficiency but might also cause anxiety from over-reliance. Third, dependence levels and demand focus varied significantly across user groups. This study proposed a novel framework explaining the emotional mechanisms and efficiency pursuits in human-AI interaction, while offering practical insights for promoting rational chatbot use and mitigating associated risks.

1 INTRODUCTION

As an essential carrier of human-computer interaction, AI chatbots are gradually penetrating all fields of human life. Integrating textual intelligence, visual pattern recognition, and predictive modeling techniques (Xie & Pentina, 2022), people use AI chatbots for daily communication and information acquisition (such as Apple Siri Assistant, Microsoft Xiaobing (Song et al., 2022), and OpenAI's ChatGPT (Haman et al., 2023; Yankouskaya et al., 2024). At the same time, its highly anthropomorphic dialogue ability and emotional interaction experience have made more and more people begin to regard AI chatbots as emotional sustenance (Xie et al., 2023). For emotional needs, companion chatbots like Replika (Ta et al., 2020; Xie & Pentina, 2022) and Mitsuku came into being. When individuals perceive that the translation of AI chatbots is sufficient to provide emotional support, encouragement, and psychological security, they will become attached to social chatbots (Xie & Pentina, 2022). Some scholars have analyzed the negative behaviors of AI users' addiction from the unique perspective of cognition-affective-conative (CAC) and proposed cognitive and emotional factors that may affect user addiction

(Zhou & Zhang, 2024). The China Academy of Information and Communications Technology (CAICT) mentioned in its Blue Book on Artificial Intelligence Governance (2024) that the increasing emotional companionship of artificial intelligence is prone to emotional dependence, which may erode human autonomy. In addition, AI chat addiction may also cause a series of psychological problems (Huang et al., 2024; Laestadius et al., 2024; Salah et al., 2024).

2 METHODOLOGY

In order to further study how emotional and efficiency needs drive users' dependence on AI chat tools', this paper adopts the method of questionnaire survey and uses quantitative analysis to explore this issue. By issuing questionnaires in the form of online answers to people who have chatted with AI agents, a total of 64 real and effective data were collected.

The preferred questionnaire analysis as a research method is mainly based on the following aspects: First, user behavior theories such as the Technology Acceptance Model (TAM) and Usage and Gratification Theory (U & G) provide a theoretical basis for understanding users' dependence on

technology. Secondly, the related research on emotion and efficiency shows that emotional needs (such as emotional support and social interaction) and efficiency needs (such as task completion speed and information acquisition convenience) are the core factors that drive users to rely on AI chat tools. Thirdly, by integrating user behavior data from AI chat platforms (e.g., ChatGPT and Google Assistant) with their real-world application scenarios, this research constructed a robust framework for context-driven questionnaire design.

Compared with other methods, questionnaire analysis has advantages in studying this topic. The questionnaire survey can systematically and efficiently collect large sample data, which is helpful to understand the basic characteristics, usage behavior, and specific performance of emotional and efficiency needs of users. In addition, users' emotional and efficiency needs can be transformed into quantifiable indicators to explore which needs dominate while revealing significant differences in dependence behavior among different groups (e.g., age, occupation status). This quantitative analysis provides rigorous statistical support and macro quantitative conclusions, making the research conclusions more convincing. In addition, it also has the advantages of strong flexibility, low cost and anonymity.

The survey instrument comprises six primary components, with the initial section dedicated to collecting participant demographic profiles. The purpose is to understand the background information of the interviewees and facilitate the subsequent analysis of group differences. The second part is the measurement of AI chat dependence behavior. Drawing on the validated 'Internet Addiction Scale', selected items were modified to operationalize AI chatbot dependency metrics in the target population. The third part is the measurement of users' emotional needs. The questions are adapted from the 'UCLA Loneliness Scale' and the 'Emotional Accompanying Needs Scale' to evaluate the emotional motivation of users using AI chat tools. The fourth part is the measurement of user efficiency requirements. The purpose is to evaluate the functional motivation of users using AI chat tools. The fifth part is the survey of group differences. The purpose is to understand the differences in dependence behavior, emotional needs, and efficiency needs among different groups. The sixth part is an open-ended question, setting up two blank-filling questions to collect users' subjective views and suggestions on AI chat tools.

Descriptive analysis, one-way ANOVA, correlation analysis, regression analysis, and multiple

comparisons — including the Least Significant Difference (LSD) method — were performed in SPSS to process the survey responses.

3 RESULTS

3.1 Basic Information

The survey achieved a 100% valid response rate (N=64), with all administered instruments meeting rigorous inclusion criteria. Participants were predominantly aged 18-25 years (50.0%), followed by those aged ≥ 46 years (21.9%). The gender distribution showed a slight female predominance (54.7%), with male participants comprising 43.8%. Regarding occupational categories, students constituted the largest group (42.2%), followed by professionals (26.6%).

3.2 The Influence of Emotional Needs and Efficiency Needs on AI Chat Dependence

According to the descriptive statistical analysis, the average score of users' AI chat tools as emotional sustenance was 2.41 (standard deviation 1.080), indicating that some users regarded AI chat tools as emotional sustenance. At the same time, the average score of users who think that AI chat tools can improve work efficiency or learning effect was 3.48 (standard deviation 1.127), indicating that users generally perceived that AI chat tools have a positive impact on efficiency.

Table 1. One-Way ANOVA Results for Effects of Emotional and Efficiency Needs on AI Chat Dependency.

Source of Variati	Sum of Squares (SS)	Degrees of Freedom	Mean Square (MS)	F	p
Between	.758	4	.189	.237	.916
Within Group	47.180	59	.800	-	-
Total	47.938	63	-	-	-

As delineated in Table 1, the linear regression analysis revealed a positive association between emotional needs ("I think AI chat tools can be my emotional sustenance") and dependency severity ($\beta = 0.201$, $p = 0.037$), confirming emotional requisites as a robust predictor of AI-mediated dependency

phenotypes. Productivity enhancement perceptions showed a robust positive correlation with dependency

levels ($\beta=0.293$, $p<0.01$), with work efficiency improvements emerging as key behavioral drivers.

Table 2. Regression ANOVA for AI Chatbot Dependency Prediction.

Source	SS	df	MS	F	p
Between Groups	13.085	2	6.542	11.451	.000 ^b
Within Groups	34.853	61	.571	-	-
Total	47.938	63	-	-	-

a. Dependent variable: What do you think of your dependence on AI chat tools?

AI chat tools can improve my work efficiency or learning effect.

b. Predictive variables: (constant) I think AI chat tools can become my emotional sustenance, I think

Table 3. Regression Coefficients for AI Chatbot Dependency Prediction.

Predictors	Unstandardized Coefficients (B)	Standard Error	Standardized Coefficients (Beta)	t	p
(Constant)	.463	.330	-	1.403	.166
"AI chatbots improve my work/study efficiency"	.293	.091	.379	3.240	.002
"AI chatbots provide emotional support"	.201	.094	.249	2.130	.037

a. Dependent variable: What do you think of your dependence on AI chat tools?

Table 4. Bootstrap Regression Analysis of AI Chatbot Dependency (BCa 95% CI).

Predictors	B	Bias	SE	Sig. (2-tailed)	BCa 95% CI
(Constant)	.463	-.011	.190	.017	[0.115,
"AI chatbots improve my work/study efficiency"	.293	.006	.079	.001	[0.112, 0.470]
"AI chatbots provide emotional support"	.201	.005	.103	.054	[0.003, 0.358]

a. Unless otherwise stated, the bootstrap results are based on 1000 stratified bootstrap samples. In the regression analysis of Table 2-4, the unstandardized coefficient of the predictive variable (emotional needs) to the degree of dependence was 0.201, and the significance level was 0.037. The results of self-sampling showed that the 95% confidence interval of emotional needs was [0.003,0.385], indicating that emotional needs had a significant impact on dependent behavior. The unstandardized coefficient of another predictor variable (efficiency demand) to dependence was 0.293, and the significance level was 0.002. The results of self-sampling showed that the 95%

confidence interval of efficiency demand was [0.112,0.470], indicating that efficiency demand had a significant impact on dependence behavior.

From the data analysis based on SPSS, both emotional needs and efficiency needs have a significant impact on dependence behavior. Among them, the unstandardized coefficient of efficiency demand (0.293) is higher than that of emotional demand (0.201), indicating that efficiency demand is more significant in driving dependence behavior.

3.3 The Influence of Dependent Behavior on Users' Mental Health, Social Ability, and Work Efficiency

3.3.1 Mental Health

Table 5. Correlation Analysis of AI Chatbot Usage Perceptions.

Measurement Variables	Pearson's r	Sig. (2-tailed)	N	Bias	SE	BCa 95% CI
1. Anxiety when unable to use AI chatbots						
Dependency level	.623**	<.001	64	.005	.085	[.421, .795]
Perceived work efficiency	.352**	.004	64	.007	.115	[.069, .598]
2. Self-reported AI dependency						
Perceived work efficiency	.468**	<.001	64	.003	.093	[.261, .641]

a. Correlations marked with ** are significant at $p < .01$ (two-tailed) **.

b. All bootstrap analyses used 1,000 stratified resamples with bias-corrected and accelerated (BCa) intervals.

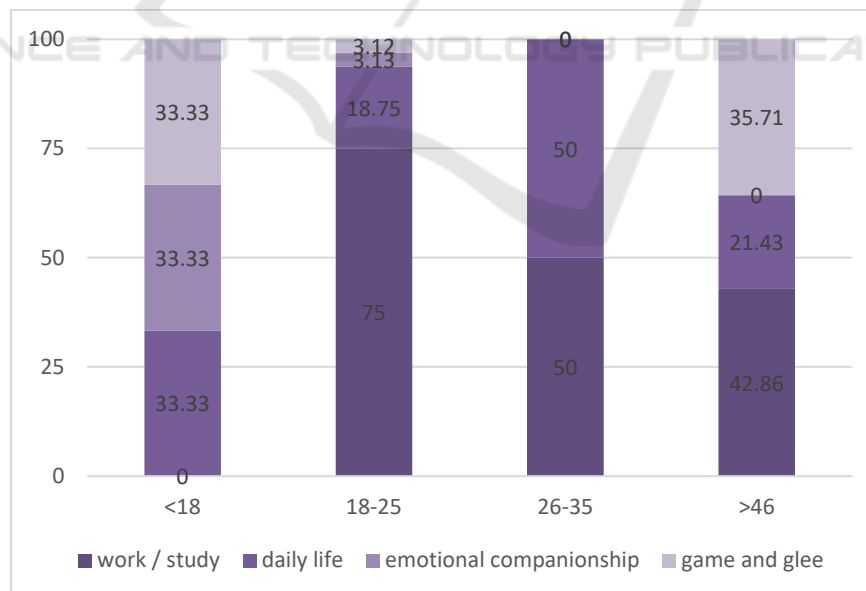
Correlation analysis showed that users would feel anxious or upset when they were unable to use AI chat tools ($r=0.623$, $p=0.000$), indicating that dependent behavior may hurt users' mental health. (See Table 5)

Users generally believe that AI chat tools can improve work efficiency or learning effect, indicating that dependence behavior has a positive impact on improving work efficiency.

3.4 Research on Group Differences

3.4.1 The Relationship Between Age and the Use of AI Chat Tools Needs and Scenarios

3.3.2 Operating Efficiency



Alt Text for Graphical Figure: A vertical bar chart illustrates the percentage distribution of four activity categories (work/study, daily life, emotional companionship, entertainment) across five age groups. The x-axis lists the age ranges: Under 18, 18-25, 26-35, 36-45, and 46+. The y-axis shows percentages from 0 to 100.

Figure 1. Age and ' What are the main scenarios for you to use AI chat tools? Cross-analysis histogram of ' problem (Photo/Picture credit: Original).

According to cross-analysis, there are significant differences in the main scenes of AI chat tools used by users of different ages. Younger users tend to seek entertainment and companionship, whereas users in middle age and beyond focus more on balancing work and leisure. (See Figure 1)

Young users (especially under 18 years old) are more inclined to chat with AI by age and emotional needs. The dependence and anxiety of AI chat tools are stronger, and with the increase in age, this dependence and anxiety gradually weaken. The attitude of the middle-aged and elderly groups is relatively conservative. This reveals that age plays a key role in how people view interactions with AI chatbots.

Age and how much people value efficiency both play a role — younger and older users tend to have noticeably different opinions on using AI chat tools. Young users have a higher acceptance of AI chat tools and are more inclined to think that AI chat tools can provide accurate information or advice, while middle-aged and elderly users show a relatively conservative attitude, especially in the age group of 26-35 years old, which may be related to their adaptability to new technologies and habits.

3.4.2 The Relationship Between Occupation and the Needs and Scenarios of Using AI Chat Tools

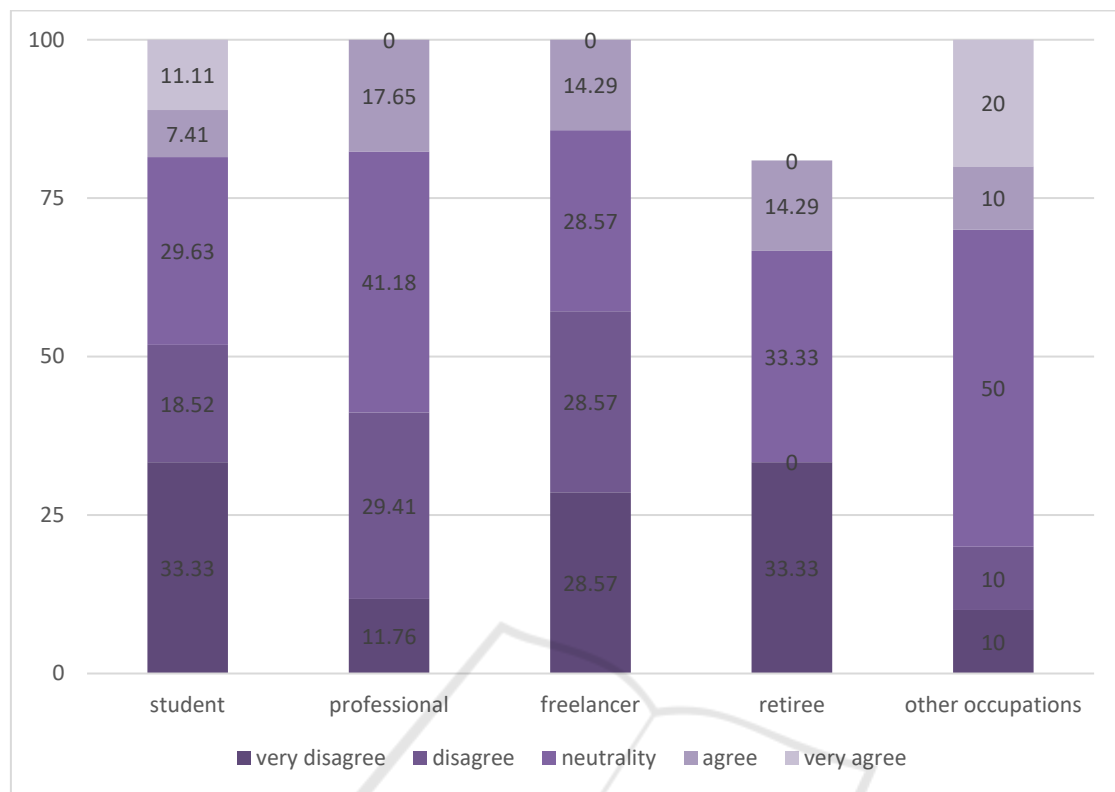


Alt Text for Graphical Figure: A vertical bar chart compares time allocation percentages across work/study, daily life, emotional companionship, and entertainment for five occupational groups (students, working professionals, freelancers, retirees, others), with segmented bars labeled numerically.

Figure 2. The cross-tabulation bar chart between occupation and "Your primary scenarios for using AI chat tools" (Photo/Picture credit: Original).

Students and professionals demonstrate a stronger propensity to utilize AI chatbots for work/study-related tasks, aligning with functional efficiency demands; conversely, freelancers and other occupational groups exhibit greater reliance on these tools for daily-life convenience and recreational

engagement, indicative of affective needs. These patterns underscore the heterogeneous demand structures and usage modalities across professional cohorts in human-AI interaction contexts. (See Figure 2)



Alt Text for Graphical Figure: A vertical bar chart compares agreement levels (strongly disagree to strongly agree) across five demographic groups (students, working professionals, freelancers, retirees, others) using segmented bars with labeled percentages for each response category.

Figure 3. The cross-tabulation bar chart between occupation and the statement "I feel anxious or uneasy when unable to use AI chat tools" (Photo/Picture credit: Original).

According to the cross-analysis between occupation and the attitude of anxiety or uneasiness when AI chat tools cannot be used, it is found that there are significant differences in emotional response among different occupational groups. (See Figure 3)

Only 7.41% and 11.11% of the students agree or strongly agree. Although 11.76% of the workplace people disagree very much, 41.18% of them feel ordinary about it. In general, students and freelancers have lower anxiety about AI tool dependence, while workplace people show more obvious anxiety tendencies. The responses of retirees and other occupational groups are more diverse. On the whole, the dependence and anxiety of occupational groups on AI tools are the most prominent.

4 CONCLUSION

4.1 The Effect of Emotional Needs and Efficiency Needs on Users' AI Chat Dependence Behavior

This study suggests that efficiency needs and emotional needs jointly drive users' dependence on AI chat tools. Among them, the leading role of efficiency needs is significant and stable, and its influence exceeds emotional needs by about 46.3%.

4.2 The Links Between AI Chat Dependence, Mental Health, Social Competence, and Workplace Effectiveness

Dependence behavior reveals a significant dual-edged impact effect: on the one hand, users generally recognized the practical value of AI tools to improve

work efficiency (average score 3.48 / 5), on the other hand, the degree of dependence and anxiety level showed a strong positive correlation ($r = 0.623$). Especially in the workplace, 41.18% of the respondents said that they would have negative emotions when they could not use AI.

Secondly, users generally believe that AI chat tools can improve work efficiency or learning effect, indicating that the high probability of dependence behavior has a positive impact on work efficiency. The study's scope was partially constrained by dataset incompleteness, limiting rigorous assessment of interpersonal skill impacts. Future research can further explore this field, such as social network analysis or influence mechanism research, in order to more fully understand the comprehensive impact of AI chat dependence behavior.

4.3 Group Difference Analysis

The analysis of group differences reveals the deep association between different groups and usage patterns. From the age dimension, although young users aged 18-25 accounted for 50% of the total sample, they showed a unique model of 'high use-low anxiety', while the user group over 46 years old showed a trend of polarization, 14.29% developed into deep dependence, and 42.86% maintained instrumental rationality. From the perspective of occupational dimension, the proportion of students using AI as a learning tool (59.3%) was significantly higher than that of other occupational groups.

4.4 Future Research Directions

In terms of group research, it can be further refined. Especially in-depth exploration of high-risk groups in the adolescent subgroup, such as adolescents with Asperger's syndrome or social anxiety characteristics. The emotional projection mechanism of these groups to AI may be significantly enhanced by neurodevelopmental differences, as shown by the case of Seville, a 14-year-old teenager in Florida who eventually committed suicide due to a long-term addiction to AI chatbots. At the same time, it is urgent to research the differentiation of occupational groups, such as comparing the differences in dependence patterns between high-pressure industry practitioners (such as programmers, health care) and freelancers.

Future emerging research topics should focus on the deep cognitive impact of human-computer interaction. It is necessary to systematically analyze the two-way effect of AI dependence on social ability: on the one hand, the long-term use of simplified

language may lead to the degradation of real communication ability, such as some users' 'trance back to the real world'; on the other hand, virtual social training in specific scenarios (such as autistic children learning social rules through AI partners) may have the value of skill transfer. In addition, the inhibitory effect of AI on creativity is worthy of attention. Excessive reliance on templated answers may weaken divergent thinking, while moderate use of AI brainstorming tools may stimulate innovative potential.

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