Appendices of the paper From Enthusiasm to Fatigue: Exploring Reduced Use and Gratification Dynamics in Intelligent System Collaboration

Full research paper

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Abstract

Following the rapid growth of General Artificial Intelligence (GAI), significant research has focused on the acceptance and use of intelligent systems, especially those enabled by GAI. However, fatigue and reduced use (even discontinuance) have received less attention despite their increasing recognition among researchers and practitioners. This fatigue, often attributed to the overwhelming influx of information and rapid advancements in artificial intelligence systems, leads many users to initially embrace these systems enthusiastically but later experience fatigue and discontinue use. Our multi-wave study examines the cross-temporal use of intelligent system by analyzing gratifications—utilitarian, hedonic, social, and technological. Our findings confirm that while initial gratification from intelligent systems is high across all types, its sustainability varies significantly depending on the nature of gratifications. This research thus provides a timely investigation, highlighting the role of individual differences in intelligence system use and calling for personalized, human-centric strategies for collaboration in business process design.

Keywords: Human-machine collaboration, Gratification, Reduced use, Technological fatigue, Cross-temporal study

Appendix 1 Demographic Analysis for the pilot study

The pilot study consisted of 129 participants, and it demostrates a near-equal gender distribution: The sample included 63 male participants, representing 48.8% of the cohort, and 66 females, accounting for 51.2%. It is noteworthy that no participants identified as 'Other' or chose not to specify their gender, indicating a potential area for more inclusive representation in future research endeavours. The educational landscape of the participants in this study was varied, encompassing a wide range of academic qualifications. The majority, 57.4% (74 individuals), possessed Bachelor's degrees, reflecting the prevalent trend of undergraduate education in today's workforce. Those with Master's degrees constituted 26.4% of the sample (34 individuals), while PhD holders formed 8.5% (11 participants). A smaller proportion, 7.0% (9 individuals), held Associate bachelor's degrees or less, and one respondent fell into the 'Other or not identified' category, highlighting the diverse educational backgrounds present in the modern workplace. In this study, the distribution of employment types mirrored the varied sectors in the current labour market. Students formed the largest group, comprising 38.8% of the sample (50 individuals). Participants employed by private companies made up a significant 25.6% (33 individuals), followed by those in state-owned enterprises, who accounted for 20.9% (27 participants). Public servants and employees of public institutions were less represented, with 4.7% (6 participants) and 7.0% (9 participants), respectively. Employees from foreign-owned enterprises were the least represented at 3.1% (4 participants). The age distribution in our sample was predominantly within the 21-30 year range, encompassing 65.1% (84 participants), also mirroring the younger demographic trend in the workforce. The 31-40 year age group included 24.0% (31 participants), and those over 41 years constituted 8.5% (11 participants). The youngest demographic, aged 0-20 years, was minimally represented at 2.3% (3 participants), aligning with my study's focus on the working-age population.

Appendix 2

To enrich our understanding beyond numeric data, we incorporated a set of open-ended questions aimed at qualitative analysis. This block of questions was designed to delve deeper into the participants' personal experiences and perceptions regarding human-machine collaboration. Specifically, we asked:

- Q1: Generally speaking, how do you feel about the idea of collaborating with intelligence systems/assistants in your work or personal life?
- Q2: Were there any challenges or difficulties that you encountered when collaborating with the intelligence systems/assistants?
- Q3: What were the biggest benefits of collaborating with the intelligence systems/assistants?
- Q4: Can you describe a time when you collaborated with an intelligence systems/assistant?

We performed qualitative analysis to corroborate our findings.

Question 1: About general feelings toward collaborating with intelligence systems, a text analysis reveals a multifaceted perspective among users. Many respondents (N=37 in T1 and N=35 in T2) express a positive attitude, emphasizing efficiency and productivity gains. They value the systems' ability to process vast amounts of data swiftly and assist with mundane tasks. However, there's cautious optimism where respondents recognize potential benefits but also express concerns about overreliance and possible impacts on creativity and jobs. Some mentioned specific applications they are comfortable with, such as Google Translate and automatic reminders. A segment of the responses (N=11 in T1 and N=2 in T2) reflects unease or reluctance, citing privacy, ethical concerns, and the authenticity of content. Others (N=11 in T1 and N=28 in T2) highlight the importance of control over technology choices, suggesting that intelligence systems should serve as tools for empowerment, not replacements. Some respondents in T2 appreciate intelligence systems for routine tasks but expect to maintain a supervisory role. A few (N=5) expressed “discomfort” and “anxiety” with more complex functionalities.

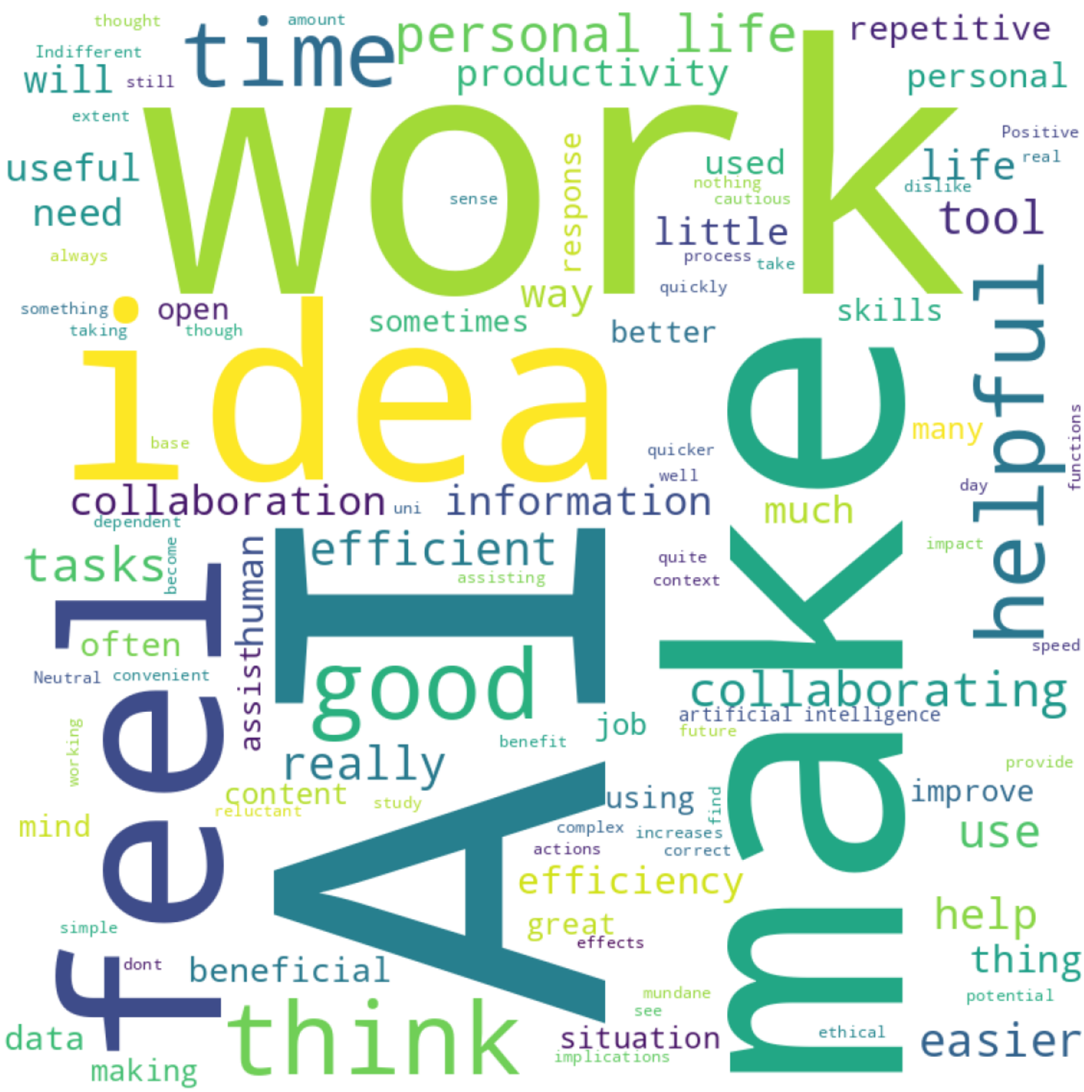

Figure 1 Word Cloud for Open Question 1

In T1, a group of participants (N=14) preferred elementary models that enhance procedures without being overly intrusive, but this preference disappeared in T2. Responses also reflect a diversity of experiences, from minimal exposure and a desire to learn more to frustrations with current capabilities. Despite varied sentiments, many users (N=21 in T1 and N=29 in T2) acknowledge the inevitability of increasing integration of intelligence systems.

Question 2: Regarding challenges or difficulties, several key themes emerged. A common challenge is the accuracy of information provided by intelligence systems. Respondents (N=21 in T1 and N=28 in T2) noted instances of incorrect or outdated information, leading to mistrust. Users often face difficulties in communicating ideas effectively, resulting in misinterpretations or overly literal responses. The systems' limited semantic understanding sometimes hinders them from providing desired outputs. There is a learning curve associated with using these systems effectively, with challenges in getting them to understand complex concepts or edit their own answers. Concerns about data privacy and security were highlighted, especially when data sharing is required. Many participants (N=38 across T1 & T2) were cautious about potential risks in data exchange. Some users (N=19 across T1 & T2) find the systems “slow,” “unresponsive,” or providing “robotic” content, indicating ongoing challenges in making interactions user-friendly. Concerns about overreliance and the potential for systems to 'take over' were also mentioned, with users (N=14 in T1 and N=25 in T2) conscious of maintaining a balance between convenience and retaining their own skills and autonomy.

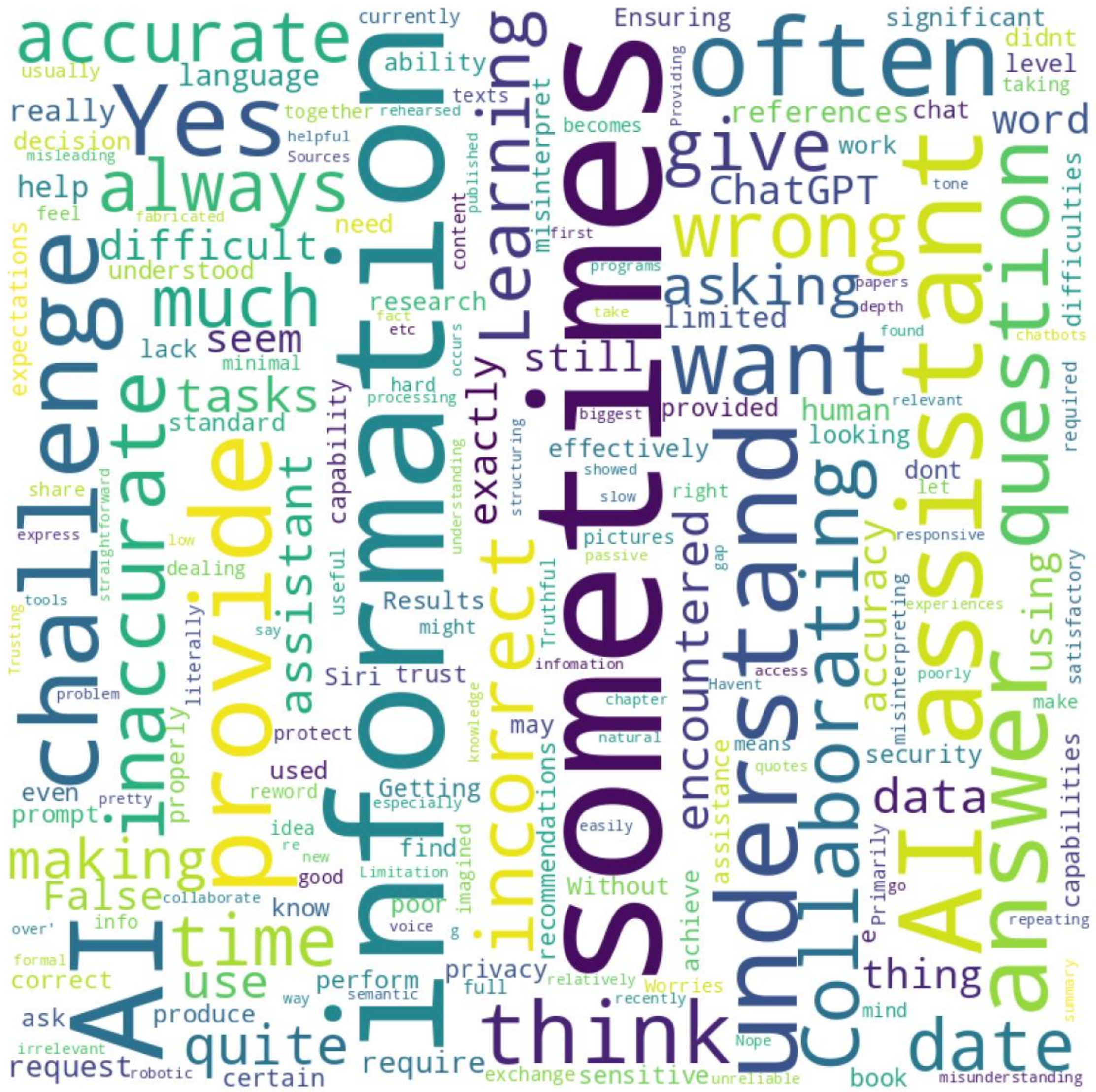

Figure 2 Word Cloud for Open Question 2

Question 3: Regarding the biggest benefits, responses highlighted "Efficiency and Productivity," "Time-Saving," and "Availability and Convenience" as dominant themes. In T2, intelligence systems' ability to organize, summarize, and analyze data was noted as beneficial for managing large datasets and gaining insights. Several respondents (N=25) recognized their role in generating ideas and providing new perspectives, helpful in creative endeavors and problem-solving. The ease and speed of accessing and consolidating information were seen as major benefits, enabling users to quickly gain necessary overviews. Many participants (N=32 in T1 and N=28 in T2) valued the support provided in academic or learning environments, where systems offer guidance and starting points for further research. Users (N=57 across T1 and T2) noted that these systems improve the quality of work by enhancing content or performing tasks faster.

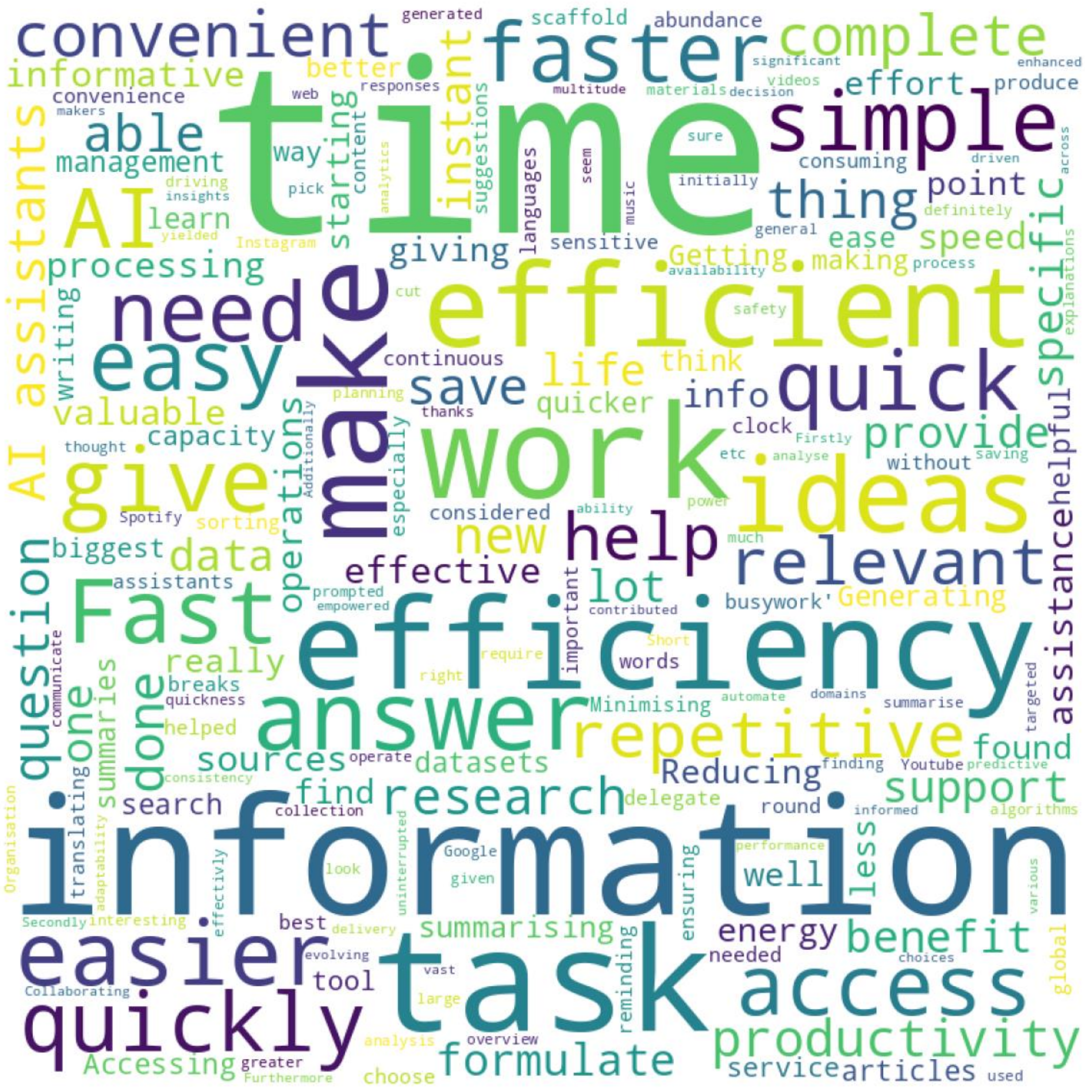

Figure 3 Word Cloud for Open Question 3

Question 4: Descriptions of collaboration experiences were vivid and diverse. One instance detailed using an intelligence system to create an optimized study timetable, showing its capability to tailor productivity tools to individual preferences. In creative realms, systems helped compose song lyrics and develop essay structures, integrating seamlessly into workflows. Some users leveraged intelligence systems for enhanced driving experiences, such as self-driving car functionalities. In professional settings, these intelligence systems were used to refine communications, helping to polish emails and written tasks. These systems were frequently harnessed for idea generation, especially in scholarly environments for brainstorming topics and gaining new perspectives. Systems were also used for translation and language learning, contributing to overcoming language barriers. In daily tasks, these systems managed schedules, set reminders, and synthesized readings, reflecting users' trust in their reliability for handling mundane tasks efficiently.

Figure 4 Word Cloud for Open Question 4

Appendix 3 Validation and Results for Pilot Study

A scree plot (see Figure 5) was generated to provide a visual aid to determine the number of factors; The plot roughly shows an "elbow" that occurs at the fourth factor.

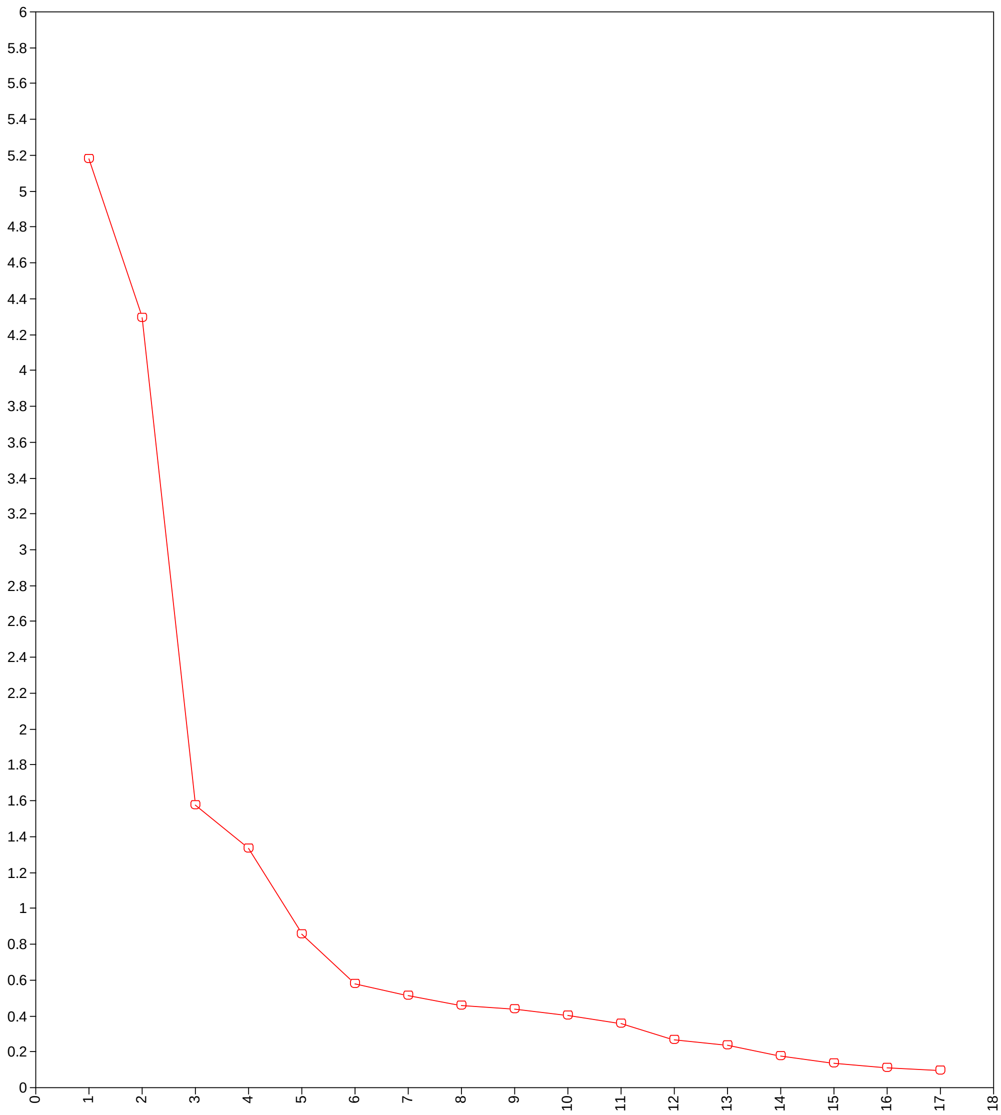

Figure 5 A Scree Plot of Pilot Study, indicating an "elbow" that occurs at the fourth factor

Item	Two factors		Three factors			Four factors			
	F1	F2	F1	F2	F3	F1	F2	F3	F4
UG1	0.549*	-0.049	0.552*	-0.041	-0.065	0.697*	0.01	-0.041	-0.173
UG2	0.741*	-0.002	0.745*	0.007	-0.069	0.715*	0.049	-0.041	0.056
UG3	0.735*	-0.046	0.741*	0.055	-0.143	0.712*	0.094	-0.114	0.058
UG4	0.355*	0.155	0.357*	-0.007	0.131	0.499*	0.031	0.149	-0.178
UG5	0.705*	-0.008	0.711*	-0.078	-0.014	0.714*	-0.031	0.011	0.008
UG6	0.728*	0.004	0.738*	-0.111	0.019	0.711*	-0.073	0.049	0.041
UG7	0.763*	0	0.773*	-0.164	0.046	0.765*	-0.113	0.071	0.029
HG1	-0.031	0.579*	-0.041	0.924*	-0.016	0.029	0.942*	-0.02	-0.104
HG2	0.001	0.603*	-0.006	0.886*	0.029	-0.025	0.878*	0.034	0.017
HG3	0.053	0.633*	0.052	0.866*	0.07	-0.007	0.856*	0.077	0.077
SG1	-0.026	0.912*	-0.021	0.045	0.887*	-0.056	0.042	0.883*	0.041
SG2	-0.013	0.869*	-0.009	0.038	0.847*	-0.039	0.04	0.842*	0.034
SG3	0.035	0.854*	0.04	-0.013	0.871*	0.023	-0.013	0.874*	0.017
SG4	0.009	0.909*	0.014	-0.003	0.924*	0.079	0.004	0.933*	-0.097
TG1	0.563*	0.11	0.573*	-0.002	0.057	-0.002	-0.044	0.062	0.856*
TG2	0.589*	0.059	0.595*	0.057	-0.034	0.08	0.033	-0.033	0.766*
TG3	0.562*	0.087	0.568*	0.064	-0.01	0.034	0.036	-0.01	0.791*

Table 1 Geomin rotated loadings, the asterisks (*) indicate significance at the 5% level.

Factors	AIC	BIC	χ^2	*df*	RMSEA	95% CI		CFI	TLI	SRMR
1	5279.5	5425.4	948.2*	119	0.232	0.219	0.246	0.421	0.338	0.227
2	4874.6	5066.2	511.3*	103	0.175	0.160	0.191	0.715	0.624	0.090
3	4664.9	4899.4	271.6*	88	0.127	0.110	0.145	0.872	0.802	0.063
4	4557.6	4832.2	136.3*	74	0.081	0.059	0.102	0.956	0.920	0.027

*Table 2 EFA Factors model fit indicators comparison, * indicate significance at the 1% level.*

Additional results (see Table 1 and Table 2) also show that the proposed four factors model was the most appropriate.

Moreover, we arrived at the following conclusions via looking at the pilot study results. First, we used IBM SPSS 24.0 to check Cronbach's alpha coefficients for our gratification factors, and they all exceeded 0.7, affirming that the scales are reliable (Pallant 2020). Then, we used MPlus 7.4 to conduct an EFA (Exploratory Factor Analysis). We firstly verified our model's validity: the model received a KMO sampling adequacy of 0.8 and a corresponding p-value<0.001 for Bartlett's Test of Sphericity, which is adequate according to Shrestha and Statistics (2021). We then followed the procedures of Fabrigar and Wegener (2011)'s procedures: A scree plot was generated to provide a visual aid in determining the number of factors; the plot roughly shows an "elbow" that occurs at the fourth factor (see Figure 5 in Appendix 3). Also, fitting mechanisms (see Appendix 3) also show that the proposed four-factor-model was the most appropriate: It not only improves the model fit indicators consistently across AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), Chi-square (χ2), RMSEA (Root Mean Square Error of Approximation), CFI (Comparative Fit Index), TLI (Tucker-Lewis Index), and SRMR (Standardized Root Mean Square Residual) but also aligns with the earlier factor loading analysis where the emergence of new patterns and a better understanding of item relationships.

Appendix 4 Means, standard deviations, and correlations for variables in Formal Study

		M	SD	1	2	3	4	5	6	7	8	9	10	11
(1)	UG	4.18	0.52	(0.789)	0.349**	0.391**	0.481**	0.112	-0.169	-0.027	0.092	0.304**	-0.203*	0.346**
(2)	HG	3.12	1.19		(0.931)	0.776**	0.410**	0.083	-0.003	0.079	0.109	0.172	-0.079	0.232*
(3)	SG	3.16	1.16			(0.926)	0.441**	0.059	-0.014	0.013	0.020	0.190	-0.098	0.236*
(4)	TG	3.90	0.77				(0.793)	0.133	-0.128	0.122	0.112	-0.054	-0.035	0.088
(5)	Age	2.05	0.22					-	-0.091	0.455**	-0.034	-0.184	-0.105	0.003
(6)	Gender	1.81	0.55						-	-0.105	-0.111	-0.006	0.275**	0.059
(7)	Education	6.02	1.03							-	0.031	-0.226*	-0.093	-0.067
(8)	Employ Type	2.45	1.71								-	0.024	0.130	-0.200
(9)	CL	2.04	0.82									-	-0.348**	0.282**

		M	SD	1	2	3	4	5	6	7	8	9	10	11
(10)	CF	3.16	1.24										-	-0.352***
(11)	CUD	3.99	0.91											-

N=96, Gender: 1 = Male, 2 = Female. Alpha reliabilities are reported in parentheses along the diagonal; Collaboration Level (CL), Collaboration Frequency (CF), and Continuance Use Delta (CUD); * p <.05, ** p <.01, *** p <.001.

Table 3 Means, standard deviations, and correlations for variables in Time 1

		M	SD	1	2	3	4	5	6	7	8	9	10	11
(1)	UG	3.69	0.58	(0.765)	0.138	0.179	0.556**	-0.05	0.042	-0.058	0.073	0.150	-0.555***	0.412***
(2)	HG	1.81	0.94		(0.954)	0.541***	0.286**	-0.004	0.005	0.248*	-0.251*	-0.137	0.020	0.011
(3)	SG	1.99	0.89			(0.829)	0.439**	-0.249*	-0.028	0.037	-0.085	0.016	-0.077	0.006
(4)	TG	3.14	0.83				(0.712)	-0.221*	0.095	-0.075	0.079	-0.029	-0.284**	0.314**
(5)	Age	2.06	0.24					-	-0.101	.520**	-0.033	-0.144	0.169	0.026
(6)	Gender	1.83	0.56						-	-0.139	-0.054	0.054	0.039	0.010
(7)	Education	6.40	0.77							-	0.173	0.012	0.034	-0.058
(8)	Employ Type	3.23	1.75								-	-0.189	-0.088	0.021
(9)	CL	1.78	0.66									-	-0.273*	0.134
(10)	CF	3.01	1.16										-	-0.268*
(11)	CUD	3.70	0.87											-

N=86, Gender: 1 = Male, 2 = Female. Alpha reliabilities are reported in parentheses along the diagonal; Collaboration Level (CL), Collaboration Frequency (CF), and Continuance Use Delta (CUD); * p <.05, ** p <.01, *** p <.001.

Table 4 Means, standard deviations, and correlations for variables in Time 2

Appendix 5 Validation of the Measurement Models for Formal Study

We conducted a series of confirmatory factor analyses to ascertain the distinctiveness of the focal variables, following the procedure suggested by Zhao and Ma (2023): We first tested the hypothesized four-factor model consisting of all items of the four constructs, which showed acceptable fit to the data based on the criteria set by (Hu and Bentler 1999). Second, we compared the four-factor model with five alternatives, presented in Table 5.

Models	**RMSEA**	**CFI**	**SRMR**	**χ^2 (df)**
Model 0: Hypothesized four-factor model	0.064, 95% CI = [0.046, 0.080]	0.945	0.077	343.305***(250) CfR = 161.389
Model 1: Triple-factor model (Combined UG and HG)	0.124, 95% CI = [0.111, 0.136]	0.789	0.142	616.731***(258) CfR=310.299

Model 2: Triple-factor model (Combined SG and TG)	0.100, 95% CI = [0.087, 0.113]	0.862	0.117	492.828***(258) CfR=239.057
Model 3: Double-factor model (Combined HG, SG and TG)	0.137, 95% CI = [0.125, 0.149]	0.736	0.134	714.647***(264) CfR=386.204
Model 4: Double-factor model (Combined UG, SG and HG)	0.151, 95% CI = [0.140, 0.163]	0.676	0.155	815.345***(264) CfR=436.830
Model 5: Single-factor model (Combined ALL gratification factors)	0.164, 95% CI =[0.152, 0.175]	0.616	0.159	921.857***(268) CfR=480.907

RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean square Residual, CFI = Comparative Fit Index, CfR = Chi-Square Contribution from Reference Group
* p < .05, ** p < .01, *** p < .001.

Table 5 Focal Factors Comparison of Main Model and Alternative Models

Appendix 6

We conducted cross-group comparisons (Measurement Invariance analysis) to observe differences in attitudes towards intelligence systems use among subjects at different points. This is necessary because of the involvement of latent variable modeling in our data collection, which leads to traditional analytical methods such as independent sample t-tests and one-factor analysis of variance to be deemed inappropriate (Meade et al. 2005). Consequently, we employed Measurement Invariance analysis for latent variables to validate the model. The fit indices and model comparisons are reported in Table 13 and 14 respectively. A series of multi-group invariance tests indicated that, although the model largely holds across metric and scalar levels, the strict model regarding factor means may not be fully invariant across groups. Following the guidelines set forth by Vandenberg and Lance (2000), the current model demonstrates sufficient measure invariance across different groups. This allows us to confidently conclude that the model retains the same meaning and underlying structure across multiple groups.

Model	**S-Bχ^2**	**df**	**CFI**	**AIC**	**RMSEA**
(A) Configural Model	552.685	335	0.879	8695.883	0.085
(B) Metric Model	568.043	348	0.878	8685.241	0.083
I Scalar Model	618.913	361	0.857	8710.111	0.089
(D) Strict Model (factor variances) for Multi-Group Invariance	627.402	365	0.855	8710.600	0.089
I Strict Model (factor mean) for Multi-Group Invariance	670.122	369	0.833	8783.146	0.095

Table 6 Multi-Group Invariance Analysis

Model Comparison	**χ^2 Difference**	**|ΔCFI|**
A *vs.* B	15.358 (13)	0.002
B *vs.* C	50.870 (13)***	0.006
C *vs.* D	8.4890 (4)	0.002
D *vs.* E	42.710(4)	0.022

Table 7 Multi-Group Invariance Model Comparisons

Appendix 7

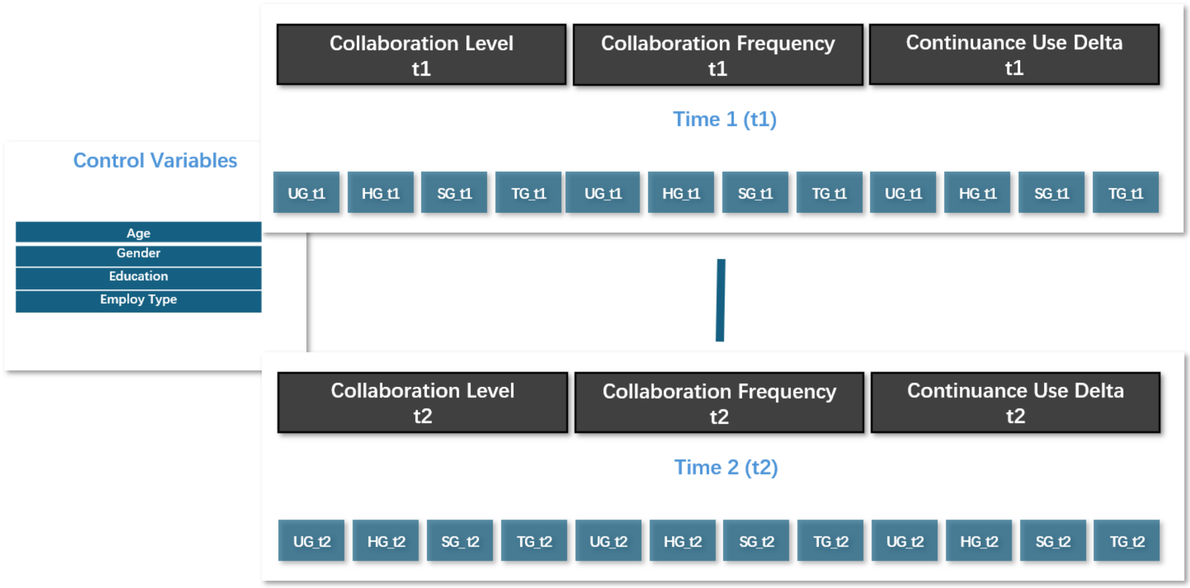

Figure 6 Research Illustration