



LLM nomads: an exploration of why users alternate among different LLMs

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Abstract

Introduction. This study explores behavioural mechanisms behind users' frequent shifting between different large language models (LLMs), analyses the factors influencing such shifting behaviour and their interaction pathways, and provides both theoretical and practical insights into user decision-making logic in multi-model interaction scenarios.

Method. Based on the Uses and Gratifications Theory, this study constructs a theoretical model, encompassing gratification dimensions, usage dimensions, and behavioural influence dimensions, and employs structural equation modelling to examine the effects of each variable on shifting behaviour.

Analysis. This study collected data from 315 valid respondents via questionnaires and analysed users' nomadic behaviour across different LLMs.

Results. The depth and professionalism of content generated by LLMs, along with users' information seeking needs, significantly and positively influence perceived usefulness, which in turn negatively suppresses shifting behaviour. Emotional and interaction experiences reduce user shifting by enhancing perceived ease of use, while user satisfaction indirectly affects shifting behaviour by shaping usage habits.

Conclusions. This study introduces the concept of "LLM Nomads" for the first time, filling a gap in research on user behaviour involving frequent shifting between models. It offers developers a practical pathway to enhance user retention, providing valuable guidance for mitigating homogeneous competition among products.

Introduction

Since OpenAI released GPT-3 in 2020, the development of Large Language Models (LLMs) has followed an exponential trajectory of iteration. The launch of ChatGPT in November 2022 marked the official entry of conversational AI into the mass consumer market, reaching 100 million registered users within two months, a record-breaking growth rate in the history of the internet (Ma et al., 2025). This milestone triggered an intense global race among tech giants. Google launched Gemini in 2023, which surpassed 50 million users within six months (Augenstein et al., 2024), leading international models such as Anthropic's Claude and Meta Llama 3 to emerge in quick succession, rapidly establishing a foothold in the AI market with their respective advantages. Meanwhile, in mainland China, domestic models like Baidu's Ernie Bot, Alibaba's Tongyi Qianwen, and DeepSeek have gained traction. These models, built on deep learning architectures with hundreds of billions of parameters, have achieved a leap from text generation to multimodal interaction, with user demographics expanding swiftly from technical developers to the public. This parallel evolution of technological iteration and market differentiation has offered global AI users a broad spectrum of choices, laying the groundwork for shifting behaviour across different models (Lee and Park, 2023).

LLM Nomads refers to a user group in the digital information environment that frequently shifts between multiple LLMs rather than being confined to a single platform. Rather than following trends blindly, these users *shift* to the platform that best fits their immediate tasks or preferences based on the distinct features, functionalities, and real-time needs of different models. According to Statista (2024), 47% of ChatGPT's monthly active users simultaneously use at least two other LLM products. This widespread behaviour carries significant implications for the development of the LLM ecosystem: from a market competition perspective, it compels developers to continuously innovate and optimise to attract and retain highly fluid users, thereby accelerating technological iteration across the industry (Qiu et al., 2024); simultaneously, it reflects the pragmatism and instrumental rationality displayed by users when engaging with general artificial intelligence (Bak & Chin, 2024). For instance, some users may choose ChatGPT for brainstorming due to its advantages in creative text generation, while applying DeepSeek to software development for its efficiency in coding. This strategic, cross-platform usage suggests that the relationship between users and AI is evolving toward a more dynamic direction.

As LLM technology matures and its application scenarios expand, understanding user shifting behaviour between multiple models has become a vital dimension of human-computer interaction research (Yang & Bao, 2025). Currently, LLMs are widely applied in various fields such as education (Jeon and Lee, 2023; Lee et al., 2024), healthcare (Boonstra et al., 2024; Deng et al., 2024; Zheng et al., 2025), and bioinformatics (Sarumi & Heider, 2024; Scheepens et al., 2024). However, a significant gap remains in existing research, which has largely focused on technical performance evaluations (O'Leary, 2024) or comparative model analyses (Ohlsson et al., 2024) but has yet to systematically and thoroughly examine the internal drivers and cognitive mechanisms that underpin the nomadic behaviour of LLM Nomads. This research void makes it difficult to explain the underlying psychological mechanisms and external triggers of user shifting under the dual pressures of rapid model iteration and increasing product homogenization. Understanding this phenomenon not only helps developers improve user retention by optimising product design but also provides a new theoretical perspective for the social sciences to observe the fragmentation and instrumentalisation of user behaviour in the digital age. Based on this, this paper aims to systematically explore the formation logic of LLM Nomads from a user perspective, focusing on answering the following three research questions:

RQ1. What factors influence users' shifting behaviour between LLMs?

RQ2. How do these factors interact to shape users' shifting pathways?

RQ3. Amid the tension between rapid LLM capability iteration and high product homogeneity, how do users cognitively form model preferences?

Literature review

Competitive landscape of the large language model market

The formation and evolution of the competitive landscape in the large language (LLM) market is the result of a dual drive from technological innovation and commercial strategies. This competitive environment serves as the prerequisite for the emergence of LLM Nomads, providing the fundamental infrastructure for user shifting behaviour and multi-model usage. At the technological level, competition centres on dimensions such as model parameter scale, multimodal processing capabilities and inference efficiency. These factors drive the industry to evolve rapidly from simple text generation toward cross-modal interaction and domain-specific customisation (Xie & Liu, 2024). While leading enterprises attempt to build technical moats in general capabilities by optimising algorithmic architectures and expanding training data (Zhang et al., 2024), smaller language models have carved out a complementary market ecosystem by offering superior efficiency and lower latency to meet specific user needs (Zhang et al., 2025). This differentiated technological development creates distinct capability boundaries between models, providing users with the objective possibility to select tools based on specific task characteristics.

Commercial strategies further reinforce market diversity, creating a richer selection space for multi-model usage. Leading companies attract developers to build ecosystems through open-source models, thereby lowering the barrier to entry. Conversely, closed-source providers like OpenAI build commercial barriers through API services and monetise traffic via enterprise subscription models (Workman et al., 2024). These differentiated strategies have fostered a stratified market structure of “general-purpose models + vertical scenarios,” where various sectors capture niche markets through customised development (Lee et al., 2024). Consequently, a product matrix characterised by multiple types and positionings has emerged. The dynamic nature of market competition leads to a continuous restructuring of model boundaries; no single model can satisfy all user needs over the long term. To maximise instrumental rationality, users inevitably bridge the functional limitations of a single model through cross-platform shifting. This constitutes the market logic behind the behaviour of LLM Nomads.

User interaction experience with large language models

User interaction experience with LLMs is an intrinsic factor driving shifting behaviour. Interaction experience covers both functional and emotional dimensions (Ahn & Seo, 2018; Chan, 2024), which directly influence users’ decisions regarding the use of multiple LLMs. In terms of functional experience, indicators such as response accuracy (Marshall et al., 2024), logical consistency (Bellini et al., 2024), and task completion efficiency (Nielsen et al., 2024) directly affect users’ assessment of its tool value. Different types of models exhibit stronger professionalism in their respective specialised fields. Through long-term use, users form a perception of the capabilities of specific models, and this differentiated perception of capabilities prompts users to actively shift models based on task types to pursue maximum efficiency (Pataranutaporn et al., 2023). Furthermore, the ease of use of the interaction interface, operational smoothness, and personalised settings also constitute important components of the experience, affecting user stickiness and shifting costs (Gartlehner et al., 2024). When a single model cannot meet the functional requirements of users’ diverse tasks, users will actively initiate shifting behaviour, helping themselves better complete tasks through a combination of multiple models.

Emotional experience focuses on users’ subjective feelings during the interaction process, including the naturalness of dialogue, the degree of human-like feedback, and the model’s depth

in understanding user needs (Zhu et al., 2025). Research indicates that users' emotional identification with a model significantly influences their intention to continue using it. This identification may stem from the personalised traits or social attributes displayed by the model during interaction, such as the emotional experience brought by highly empathetic conversational capabilities (Qian et al., 2025). If a certain LLM causes an uncomfortable experience during use, users will turn to other products that can provide them with a better experience. Additionally, over long-term use, users may adjust their usage preferences for these models due to fluctuations in performance or functional updates, forming a shifting decision-making mechanism based on real-time experience (Atzil-Slonim et al., 2024). In summary, as a precursor factor for LLM users to shift between different products during use, interaction experience plays an important role.

Use and gratifications theory

Uses and Gratifications theory (U&G) provides a theoretical framework for explaining the shifting behaviour and multi-model logic of LLM Nomads, clearly revealing the internal motivational mechanisms of user nomadic behaviour. Proposed by Elihu Katz (1973) and other scholars in the 1970s, the theory's core premise treats the audience as proactive subjects with agency. It suggests that individuals actively select and use media or content to satisfy specific needs based on their cognitive, affective and social requirements. The applicability of this theory has been validated across various digital technology scenarios, such as the continuous usage intention of generative AI (Qiu et al., 2025) and social media user behaviour (Li et al., 2021). Its perspective aligns highly with the phenomenon of LLM Nomads.

In the context of LLMs, core user needs can be clearly categorised into instrumental and social needs (Nash, 2024). Instrumental needs encompass practical goals such as information retrieval, task processing, and professional content generation, while social needs include emotional and social aspirations like companionship, creative collaboration, and self-expression. Differences in functional design allow various models to develop specific instrumental attributes; for instance, some models focus on the efficient fulfilment of instrumental tasks, while others emphasise optimising the experience of social needs (Orwig et al., 2024). Because a single model can rarely cover a user's diverse requirements, users (driven by need fulfilment) actively engage in multi-model usage and shifting. By dynamically migrating between models, they combine the strengths of different platforms to achieve comprehensive gratification. This strategic selection behaviour aligns perfectly with the core logic of Uses and Gratifications theory. It not only reflects a pragmatic attitude toward technological tools but also theoretically validates the rationality of LLM Nomads' behaviour, providing a solid foundation for the subsequent discussion on the formation mechanisms of nomadic behaviour.

Research model and hypothesis development

This study focuses on users of LLMs and, from the perspective of the Uses and Gratifications Theory, constructs a model of influencing factors behind the shifting behaviour of LLM Nomads. The factors involved are categorised into three dimensions: gratification, usage, and behavioural influence. The gratification dimension includes factors such as content depth and specialisation, as well as information seeking needs. These represent the users' motivations and starting points for engaging with LLMs, reflecting their considerations of how well the models satisfy their demands for knowledge depth and information acquisition. The usage dimension encompasses emotional experience and interaction experience. It explores the impact of the system on user perceptions in terms of ease of use and affective interaction, based on users' experiences during the use of LLMs. Building upon this, other relevant factors specific to the study's context are categorised under the behavioural influence dimension. This dimension approaches the issue from the perspective of users' perceptions, investigating how factors such as perceived usefulness, ease of use and usage habits affect users' shifting behaviour among different LLMs.

Gratification dimension

Depth and specialisation reflect the characteristics of LLMs in terms of knowledge reserves and accuracy of responses, serving as critical criteria for users to judge whether a model can meet their task requirements. Previous research has shown that students' perceived usefulness of video conferencing technology is closely tied to the professional layout of the platform interface; more professionally designed digital tools are more likely to attract their preference (Yazici, 2025). In the realm of commercial consumption, consumers' perceptions of the usefulness of online reviews are also influenced by the depth of the reviews and the expertise of the reviewers, which in turn affects their purchase intentions (Zhu et al., 2022). The deeper and more specialised the content generated by a LLM, the more likely users are to perceive it as useful.

Information seeking needs reflect users' desire to efficiently obtain the information they require through the model. Using grounded theory, Zhai and Han (2024) explored the driving factors behind information exchange in online health communities and found that the demand for health-related information was directly associated with the perceived usefulness of these communities, subsequently influencing users' platform selection and interaction behaviour. In the context of LLM usage, if a model demonstrates deep, specialised knowledge that meets users' needs for solving complex problems or helps them efficiently retrieve diverse information, it will enhance users' perception of the model's usefulness.

Based on the above analysis, this study proposes the following hypotheses:

H1. Depth and specialisation have a significant impact on users' perceived usefulness of LLMs.

H2. Information seeking needs have a significant impact on users' perceived usefulness of LLMs.

Usage dimension

Emotional experience reflects the emotional responses users develop while interacting with LLMs, such as feelings of pleasure or trust. In the use of various digital products, positive emotional experiences can improve users' evaluations of ease of use and enhance their willingness to continue using the product (Wu & Holsapple, 2014). When users engage with LLMs, if the model responds in a friendly manner, shows emotional understanding and offers appropriate feedback, users are more likely to perceive the model as easy to use, thereby gaining a positive emotional experience.

Interaction experience refers to the fluency and response speed during the interaction between users and the model. In human-computer interaction research, the smoothness and efficiency of the interaction process are key factors shaping users' perceptions of system usability. This relationship has been confirmed in studies on interactive video retrieval (Albertson & Ju, 2016). Similarly, if a LLM responds quickly, features a clean and user-friendly interface, and provides intuitive operational procedures, users will not need to expend excessive effort on adaptation and learning, which can significantly enhance their perceived ease of use.

Based on this, the study proposes the following hypotheses:

H3. Emotional experience has a significant impact on users' perceived ease of use of LLMs.

H4. Interaction experience has a significant impact on users' perceived ease of use of LLMs.

Behavioural influence dimension

Perceived usefulness reflects users' recognition of the actual value brought by LLMs. As a classic variable measuring user acceptance during the emergence of new technologies, the role of perceived usefulness has been validated in numerous studies. Xue et al. (2021), based on the ECM-ISC model studying knowledge payment apps, found that perceived usefulness directly affects user satisfaction and continued usage intention, and can also have an indirect effect through flow experience, making it a crucial factor influencing continuous use. In the field of mobile libraries, Guo and Ming (2020) constructed an integrated model and empirically discovered that initial perceived usefulness is influenced by task-technology fit and expectation confirmation, while later it relates to system, information and service quality; throughout, it consistently affects user satisfaction and continued use intention. When users feel that LLMs effectively meet their needs in knowledge answering and other aspects, they are more likely to continue using the model and reduce shifting behaviour. Conversely, low perceived usefulness may lead users to frequently try other models. The degree of perceived usefulness is directly related to the fulfilment of users' internal expectations (Qiu et al., 2025). If a model can satisfy users' diverse and complex needs through deep expertise and efficient information provision, users are more likely to experience high satisfaction.

Based on this, the study proposes the following hypotheses:

H5. Perceived usefulness has a significant impact on users' shifting behaviour among LLMs.

H6. Perceived usefulness has a significant impact on users' satisfaction with LLMs.

Perceived ease of use concerns users' feelings about the operational convenience and interaction friendliness of LLMs. In AI application fields, research has shown that middle school students' continued intention to use AI learning platforms is influenced by perceived ease of use and self-efficacy (Zhai et al., 2022). When a new product is first introduced, unfamiliarity may deter new users; at this point, perceived ease of use becomes a key breakthrough for market acceptance. If a LLM is easy to operate and provides smooth interaction, users are more likely to continue using it due to lower usage costs, thus reducing shifting behaviour. Similarly, the impact of perceived ease of use on satisfaction has long been documented; for example, enterprises' use of Enterprise Resource Planning (ERP) systems is significantly affected by perceived ease of use, where a simple and efficient system experience often enhances employee satisfaction (Amoako-Gyampah, 2007). During the use of LLMs, a clean interface and fast text generation features typically provide good experiences and improve user satisfaction.

Based on this, the study proposes the following hypotheses:

H7. Perceived ease of use has a significant impact on users' shifting behaviour among LLMs.

H8. Perceived ease of use has a significant impact on users' satisfaction with LLMs.

Users' satisfaction with LLMs shapes their subsequent usage tendencies. Prior experience and satisfaction with information technology influence users' habitual use of new technologies, causing them to subconsciously follow previous usage patterns during interaction (Lankton et al., 2010). Consumer satisfaction with shopping is also closely related to their habitual shopping times, with fixed shopping time habits providing better experiences (Zhang et al., 2021). High satisfaction indicates that a LLM meets user needs in functionality and experience, encouraging users to form usage habits. Regarding the influence of usage habits on shifting behaviour, Chen et al. (2022), combining information system motivation theory and planned behaviour theory to explore continued use intention of mobile social media services, found that habits play an

important role in social media usage, and new social media platforms often struggle to gain user favor due to past habits. When users develop a habit of using a certain LLM, behavioural inertia and psychological dependence emerge, reducing shifting behaviour to avoid the costs of adapting to new models.

Based on the above analysis, the study proposes the following hypotheses:

H9. Satisfaction has a significant impact on users' usage habits of LLMs.

H10. Usage habits have a significant impact on users' shifting behaviour among LLMs.

Based on the previous analysis and the application of Uses and Gratifications theory, the model of influencing factors for LLMNomads' shifting behaviour constructed in this study is shown in Figure 1.

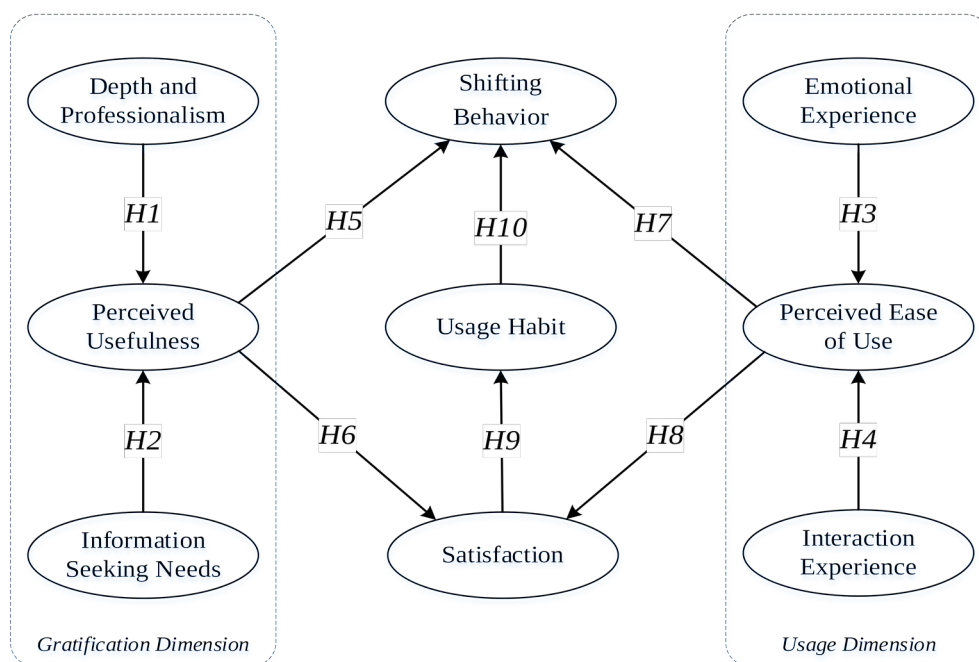


Figure 1. The research model of influencing factors on the shifting behaviour of LLM Nomads

In this model, the gratification dimension corresponds to the instrumental and informational needs actively sought by users in the Uses and Gratifications theory, serving as the fundamental motivation for model selection. The usage dimension follows these needs, reflecting the perceptual experience during the process of use as defined by the theory; it acts as the critical link between needs and actions. Finally, the behavioural influence dimension serves as the concretisation of the theory's *need fulfilment-experience feedback-behavioural decision* closed loop. These three dimensions progress according to the sequence of *need triggering-experience regulation- behaviour generation*, providing a comprehensive explanation of the behavioural formation mechanism within the theoretical framework.

Method

Research sample

This study aims to investigate the influencing factors of the shifting behaviour among LLM Nomads and the interrelationships between these factors. All respondents have experience using at least two different LLMs and exhibit cross-platform shifting behaviour, which aligns with the

defined scope of LLM Nomads and ensures that the research subjects precisely match the study's theme. During the empirical research phase, the research team designed an online survey tool using the Wenjuanxing platform. Questionnaires were distributed through multiple channels—including tech communities, professional networks, and university groups—to cover users of varying ages, occupations, and usage scenarios, thereby mitigating sampling bias associated with any single channel. A random sampling survey was implemented targeting the population with LLM experience. Ultimately, 346 questionnaires were collected. Following data cleaning to exclude 31 invalid responses characterised by abnormal completion times or incomplete information, 315 valid questionnaires were retained as the analysis sample. The effective recovery rate of the questionnaire reached 91%.

The descriptive statistics of the data are presented in Table 1. It can be seen that, in terms of demographic characteristics, the gender distribution is balanced; the age group of 26–45 years old accounts for a significant proportion; and the educational background is mainly undergraduate level. Data on device usage preferences indicate that most users interact with LLMs via computer and mobile terminals. The above sample characteristics highly align with the research design requirements, indicating good representativeness of the data. Additionally, this study has been approved by the Ethics Review Committee of the affiliated institution, which concluded that the research protocol complies with the Code of Academic Ethics and poses no risk of infringing participants' rights.

Statistical items frequency		Percentage(%)
Gender		
Male	150	47.6
Female	165	52.4
Age		
18 ~	50	15.9
25 ~	98	31.1
35 ~	89	28.3
45 ~	57	18.1
55 years and above	21	6.7
Education level		
high School and below	78	24.8
College	79	25.1
university undergraduate	135	42.9
master's degree	19	6.0
doctoral and above	4	1.3
Common types of devices		
Mobile phones	108	34.3
Computers	136	43.2
Tablets	71	22.5

Table 1. Basic information of the sample data

Survey instruments and measures

This study, based on a well-established scale system from existing literature and combined with expert consultation, developed an initial questionnaire for data collection on the influencing factors of LLM Nomads' shifting behaviour. The questionnaire consists of two parts: a user basic information module and a measurement items module. The measurement items adopt a widely used 7-point Likert scale in academia, with scores ranging from 1 to 7 corresponding to semantic gradients from *strongly disagree* to *strongly agree*. To ensure the reliability and validity of the questionnaire, the study conducted a pilot survey with sixteen university teachers and graduate

students experienced in using LLMs. The questionnaire items for each influencing factor and their corresponding sources are shown in Table 2.

Construct	Questions	Source
Satisfaction degree	I am satisfied with the information generated by LLMs	Wu and Zhang (2023)
	The process of using LLMs brings me pleasure	
	I find LLMs very useful	
Usage habit	For me, using LLMs has become a habit	Shivdas et al. (2020)
	For me, I have become proficient in using LLMs	
	For me, using LLMs has become commonplace	
Depth and professionalism	The quality of content generated by LLMs is highly in-depth	Nadiv and Kuna (2025)
	The quality of content generated by LLMs is highly professional	
	The content generated by LLMs is very accurate	
	The content generated by LLMs is very comprehensive	
Information seeking needs	Using LLMs can help me access different types of information	Uddin et al. (2021)
	Using LLMs allows me to learn more knowledge	
	Using LLMs can improve the efficiency of my information acquisition	
	Using LLMs enables me to obtain information easily	
Emotional experience	Using a new LLM causes emotional fluctuations in me	Hanson et al. (2024)
	Using a new LLM makes me feel curious	
	The process of using LLMs gives me a sense of companionship	
	I think LLMs have rich emotions	
Interactive experience	The response speed of content generated by LLMs is very fast	Chen et al. (2025)
	The stability is high during the content generation process of LLMs	
	LLMs have strong contextual understanding capabilities in content generation	
Perceived usefulness	The information integration efficiency of LLMs is very high	Alajmi and Ali (2023)
	LLMs have improved my work and learning abilities	
	Using LLMs has saved my time costs	
Perceived ease of use	The operation interface of LLMs is simple	Marasinghe et al. (2024)
	The operation process of LLMs is convenient	
	LLMs have good fault tolerance for instructions	
Shifting behaviour	I tend to try using multiple LLMs	Yang et al. (2022)
	I have experience using multiple LLMs	
	I shift between using multiple LLMs simultaneously	

Table 2. Initial content and item references to the Questionnaire

Data analysis and results

This study employs Structural Equation Modeling (SEM) to construct a precise path model that holistically examines both the direct and indirect factors influencing users' shifting behaviour across different LLMs. The SEM approach offers a systematic perspective for uncovering the mechanisms through which factors such as satisfaction, usage habits, and information seeking needs impact users' model-shifting behaviour. The research process begins with an evaluation of the measurement model to ensure the constructs exhibit reliable validity and internal consistency. Subsequently, the structural model is tested to verify the hypothesised relationships within the proposed framework of influencing factors on LLM nomads' shifting behaviour, thereby reinforcing the scientific rigor and credibility of the study's conclusions.

Measurement model

This study utilised SPSS 27.0 to conduct factor analysis on the sample data and employed Cronbach's Alpha and Composite Reliability (CR) to assess reliability. The results are presented in Table 3. Generally, when the overall Cronbach's Alpha and CR values of the observed variables reach or exceed 0.7, the data can be considered to have good reliability (Straub and Gefen, 2004). In this research context, the Bartlett's test of sphericity yielded a Chi-square significance level of 0.000, indicating that the sample data is suitable for factor analysis. Additionally, the Kaiser-Meyer-Olkin (KMO) value was 0.881, surpassing the 0.7 threshold set by statistician Kaiser. The overall Cronbach's Alpha for the sample data was 0.917. As shown in Table 3, the Cronbach's Alpha values of the individual observed variables ranged from 0.791 to 0.867, all above 0.7. The CR values also exceeded the 0.7 benchmark. In sum, the sample data in this study demonstrates high reliability and successfully passed the reliability test.

Variables	Title code	Standard load	Cronbach's Alpha	CR	AVE
Satisfaction degree	SD1	0.750	0.817	0.807	0.582
	SD2	0.753			
	SD3	0.786			
Usage habit	UH1	0.808	0.835	0.834	0.626
	UH2	0.779			
	UH3	0.787			
Depth and professionalism	DP1	0.801	0.849	0.849	0.584
	DP2	0.735			
	DP3	0.777			
	DP4	0.741			
Information seeking needs	ISD1	0.806	0.867	0.867	0.620
	ISD2	0.777			
	ISD3	0.772			
	ISD4	0.793			
Emotional experience	EE1	0.803	0.858	0.858	0.601
	EE2	0.781			
	EE3	0.754			
	EE4	0.763			
Interactive experience	IE1	0.830	0.826	0.826	0.613
	IE2	0.771			
	IE3	0.746			
Perceived usefulness	PU1	0.748	0.823	0.821	0.605
	PU2	0.776			
	PU3	0.808			
Perceived ease of use	PEU1	0.741	0.791	0.785	0.549
	PEU2	0.734			
	PEU3	0.747			
Shifting behaviour	SB1	0.740	0.800	0.788	0.554
	SB2	0.779			
	SB3	0.712			

Table 3. Factor loadings, variable values of measurement Indicators

Validity testing, as a key approach to evaluating the effectiveness of a measurement model, is primarily assessed from two dimensions: content validity and construct validity (Straub and Gefen, 2004). In terms of content validity, all questionnaire items in this study were developed based on well-established scales from prior research. Additionally, a pilot study was conducted to revise and refine the questionnaire before formal distribution. Therefore, the questionnaire is considered to possess good clarity and validity. Construct validity comprises convergent validity and discriminant validity. Regarding convergent validity, it is generally accepted in academic research that when the Average Variance Extracted (AVE) exceeds 0.5, the observed variables demonstrate good convergent validity. As shown in Table 3, the AVE values for all variables in this study are above 0.5, indicating strong convergent validity of the observed variables. For discriminant validity, it is evaluated by comparing the square root of the AVE values with the correlation coefficients among the observed variables. As presented in Table 4, the square root of each variable's AVE is greater than the absolute value of its correlation coefficients with other

variables, which fully supports the presence of good discriminant validity among the observed variables.

	SD	UH	DP	ISD	EE	IE	PU	PEU	SB
SD	0.763								
UH	0.439	0.791							
DP	0.222	0.097	0.764						
ISD	0.210	0.092	0.373	0.787					
EE	0.203	0.089	0.363	0.450	0.775				
IE	0.228	0.100	0.457	0.396	0.344	0.783			
PU	0.334	0.147	0.496	0.451	0.277	0.297	0.778		
PEU	0.393	0.173	0.245	0.246	0.367	0.423	0.169	0.741	
SB	-0.307	-0.351	-0.217	-0.205	-0.192	-0.215	-0.338	-0.357	0.744

Table 4. Correlation coefficient and the square root of the average variance extracted (AVE)

Common method biases refer to the measurement error that arises from using the same data source, rater, measurement context, item context, or item characteristics (Chin et al., 2012). This type of bias is particularly prevalent in empirical research scenarios that rely on self-reported survey data. Significant common method bias may compromise the accuracy of research conclusions. Given that this study collected data solely through questionnaire surveys, there is a potential risk of common method bias. To address this, the widely adopted Harman's single-factor test was employed to assess the extent of such bias. The test results showed that the variance explained by the first (largest) factor was 29.39%, which is below the critical threshold of 50%. This indicates that serious common method biases were not present, and the collected data are suitable for subsequent analyses.

Structural model

To assess the validity and reliability of the theoretical model, this study employed the structural equation modeling software AMOS 26.0 to construct a detailed path diagram of the influencing factors of LLMNomads' shifting behaviour. The collected data were then imported into the model for verification, and the test results are presented in Figure 2.

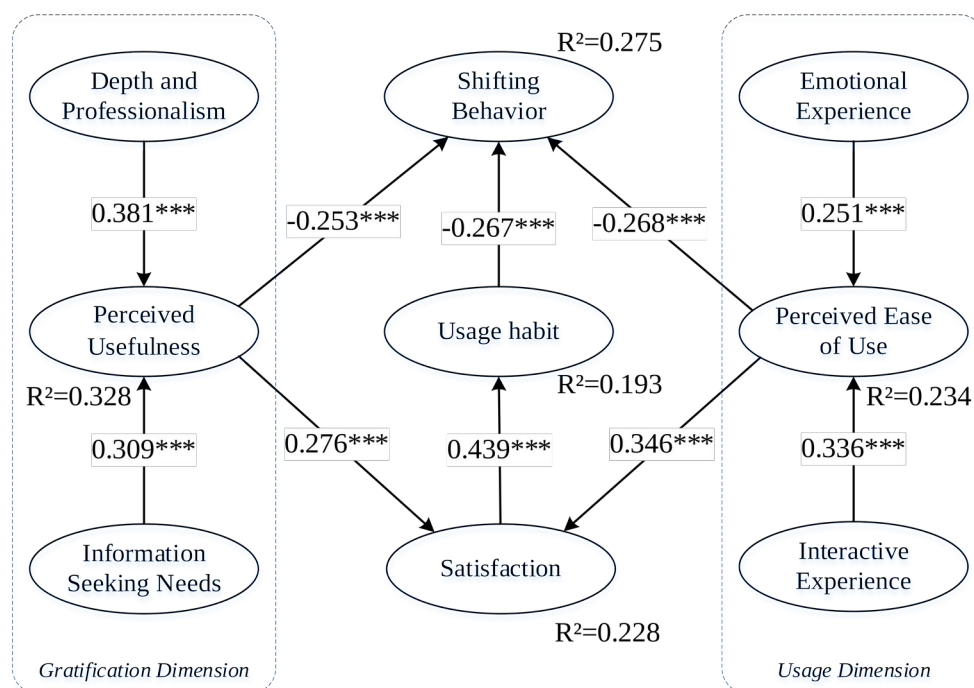


Figure 2. Standardised path coefficients of the influence model

This study set the significance level at $p = 0.05$. The path coefficients between latent variables shown in Figure 2 represent standardised regression weights, where the magnitude reflects the strength of influence exerted by the observed variables on the latent constructs. The analysis revealed that the absolute values of all observed variables' path coefficients range from 0.251 to 0.439, indicating a good overall model fit. Specifically, the direct effects of perceived usefulness, perceived ease of use, and usage habit on shifting behaviour are $\beta = -0.253$, $\beta = -0.268$, and $\beta = -0.267$, respectively. These effects are not only statistically significant but also aligned in direction. In addition, depth and professionalism, information seeking needs, emotional experience, interactive experience, and satisfaction exert indirect effects on shifting behaviour through perceived usefulness, perceived ease of use, and usage habit.

The squared multiple correlations labelled next to the endogenous variables indicate the proportion of variance in each dependent variable explained by its predictors. As shown in Figure 2, perceived usefulness, perceived ease of use, and usage habit together account for 27.5% of the variance in shifting behaviour. Depth and professionalism and information seeking needs together explain 32.8% of the variance in perceived usefulness; emotional experience and interactive experience explain 23.4% of the variance in perceived ease of use; perceived usefulness and perceived ease of use jointly account for 22.8% of the variance in satisfaction; and satisfaction alone explains 19.3% of the variance in usage habit. These findings demonstrate the model's effectiveness in explaining the variability among latent constructs.

Model fit indices are presented in Table 5, and the key indicators confirm a good fit between the model and the data. The values listed in the table meet the conventional criteria, indicating that the model demonstrates a high degree of fit and overall robustness.

Adaptability index	Statistic value	Optimal standard value	Model fit
CMIN/DF	1.524	<2.0	Excellent
RMSEA	0.041	<0.05	Excellent
GFI	0.893	>0.9	Acceptable
CFI	0.952	>0.9	Excellent
IFI	0.952	>0.9	Excellent
TLI	0.946	>0.9	Excellent
NFI	0.873	>0.9	Acceptable

Table 5. Summary of model fitness tests

Note(s): “CMIN/DF” indicate the chi-square freedom ratio; “RMSEA” indicate the progressive residual mean square and square root; “GFI” indicate the benign fit index; “CFI” indicate the comparison of fitness index; “IFI” indicate the value-added adaptation index; “TLI” indicate the Tucker-Lewis index; “NFI” indicate the Normalized fitting index.

Discussion

This study, grounded in the Uses and Gratifications Theory, investigates the influencing mechanisms underlying the shifting behaviour of LLM Nomads. By employing structural equation modeling, the analysis validates the direct and indirect effects of multidimensional factors, such as depth and professionalism, and information seeking needs, on users’ cross-model shifting behaviour. The findings reveal users’ decision-making logic in the context of rapid technological iteration and product homogenization, offering a new perspective for understanding the evolving patterns of human–AI interaction.

Discussion of results

Based on the path analysis results among variables in the revised model of influencing factors for nomadic user shifting behaviour in LLMs (Figure 2), the following conclusions can be drawn.

First, Uses and Gratifications theory emphasises that instrumental needs are the core drivers of media selection. The results of this study show that Depth and professionalism ($\beta=0.381$) and Information seeking needs ($\beta=0.309$) have significant positive effects on Perceived usefulness, which is a concrete manifestation of this hypothesis. From a theoretical perspective, depth and professionalism correspond to the user’s demand for high-quality information supply; the higher the professionalism and precision of the model-generated content, the better it satisfies the user’s instrumental demands in complex tasks, thereby strengthening their perception of the model’s usefulness. Meanwhile, information seeking needs directly echo the information acquisition motives in Uses and Gratifications theory. A model’s efficient information integration and supply capabilities can effectively reduce search costs, allowing users to perceive the practical value of the technological tool. Together, these two factors form the decision-making basis for model selection based on instrumental needs, confirming the logical relationship of “needs-driven media selection” within Uses and Gratifications theory.

Second, Uses and Gratifications theory focuses not only on the fulfilment of instrumental needs but also on the emotional and experiential perceptions during the usage process. In this study, the significant positive influence of Emotional experience ($\beta=0.251$) and Interaction experience ($\beta=0.336$) on Perceived ease of use perfectly illustrates this theoretical dimension. Regarding emotional experience, the anthropomorphic feedback and sense of companionship provided by the model align with the user’s social needs; this emotional resonance reduces the psychological distance from the technology, leading to a subjective perception of ease of use. Regarding interaction experience, functional indicators such as response speed and context understanding directly affect user efficiency and cognitive load. An efficient and smooth interaction process

reduces operational costs, strengthening the judgement of ease of use from an objective level. This result extends the application of Uses and Gratifications theory to human-computer interaction scenarios, indicating that instrumental and emotional experiences collectively constitute the user's evaluation system for media usage.

Finally, Uses and Gratifications theory posits that the degree of need fulfilment and usage experience collectively influence subsequent behavioural decisions. In this study, the significant negative effects of Perceived usefulness ($\beta = -0.253$), Perceived ease of use ($\beta = -0.268$), and Usage habits ($\beta = -0.267$) on shifting behaviour, as well as the path where Satisfaction indirectly acts on shifting behaviour through Usage habits ($\beta = 0.439$), fully validate this theoretical logic. From a mechanistic standpoint, perceived usefulness and perceived ease of use correspond to need fulfilment and usage experience, respectively. When a model sufficiently meets instrumental needs and is convenient to use, users develop stable usage preferences and a reduced intention to shift across platforms; this reflects the theoretical principle that *media gratification reinforces continuous usage behaviour*. Furthermore, the role of satisfaction in shaping usage habits highlights the closed-loop logic of Uses and Gratifications theory: users achieve high satisfaction through need fulfilment and positive experiences, which in turn solidifies usage habits and ultimately inhibits shifting behaviour through behavioural inertia. Simultaneously, this transmission path reveals the explanatory power of Uses and Gratifications theory in long-term behavioural prediction—namely, that a user's continuous selection of media stems not only from immediate gratification but also from the habituation formed by long-term experience.

Theoretical and managerial implications

Based on the Uses and Gratifications Theory, this study constructs a model of influencing factors for nomadic user shifting behaviour in LLMs, offering three theoretical contributions.

First, while existing research largely focuses on the technical performance of LLMs or user acceptance of individual models, it rarely addresses user shifting behaviour across multiple models. This study introduces, for the first time, the concept of LLM nomads, revealing the underlying logic behind LLM Nomads' shifting among models such as ChatGPT and DeepSeek. In doing so, it fills a theoretical gap in the study of multi-model interaction behaviour and enriches the theoretical system of user behaviour in the field of human-computer interaction. Second, by incorporating factors such as depth, professionalism and information seeking needs into the Uses and Gratifications Theory framework, this study demonstrates through empirical analysis that users' instrumental needs and emotional experiences influence shifting behaviour via mediating variables such as perceived usefulness and perceived ease of use. This finding expands the theoretical boundaries of Uses and Gratifications Theory in the context of AI and offers a novel perspective for understanding cross-platform user decision-making. Third, while prior research offers limited exploration of habit formation mechanisms, this study confirms that satisfaction indirectly suppresses shifting behaviour by fostering usage habits, thereby revealing a *satisfaction-habit-behaviour* transmission pathway. This conclusion supplements existing literature on long-term behavioural prediction and highlights the theoretical importance of habit as a driver of user behaviour.

Based on the research findings, developers of LLMs should accurately grasp the core logic behind the cross-model shifting of LLM Nomads and optimise product strategies centred on need fulfilment. At the product level, they should focus on vertical domains to strengthen content depth and professionalism, while establishing efficient information retrieval channels to precisely match instrumental needs and enhance perceived usefulness. Meanwhile, they should optimise interaction fluency and emotional feedback mechanisms through anthropomorphic responses and streamlined interfaces, to bridge user experience gaps. Regarding user operations, developers need to construct a closed loop of *need matching*, *satisfaction enhancement*, and *habit solidification* by iterating core functions based on behavioural data and enhancing satisfaction

through personalised services to cultivate usage habits and reduce shifting intentions. In the context of market competition, firms should implement differentiated positioning based on core model strengths to avoid homogenized competition while establishing behaviour monitoring systems to identify shifting signals like multi-model parallel usage, ultimately improving user retention through data migration and exclusive features to build core competitive barriers in a dynamic environment.

Conclusion

This study centres on the shifting behaviour of LLM Nomads, constructing an influencing factor model grounded in the Uses and Gratifications Theory. Through structural equation modelling, it empirically verifies how multiple factors shape users' cross-model shifting behaviour. The findings reveal that depth and professionalism as well as information seeking needs suppress shifting behaviour by enhancing perceived usefulness, while emotional experience and interaction experience reduce users' shifting tendencies by improving perceived ease of use. Furthermore, satisfaction indirectly influences shifting behaviour by shaping usage habits, forming a behavioural logic chain of *need fulfilment* → *experience optimisation* → *habit consolidation*. The results unveil a utilitarian decision-making logic under conditions of rapid technological iteration and product homogenization: LLM Nomads seek to maximise both instrumental value and emotional experience through multi-model shifting. This conclusion not only enriches the theoretical understanding of user behaviour in the field of human-computer interaction but also provides empirical evidence for LLM developers to optimise product design and enhance user retention.

Despite offering a novel perspective on users' shifting behaviour, this study has certain limitations. First, as it relies on cross-sectional data, it cannot capture the dynamic evolution of user behaviour over time. Future research could adopt longitudinal methods to track how technological updates or model iterations influence shifting behaviour in real time. Second, the proposed model does not sufficiently account for the influence of external environmental factors such as market competition strategies or regulatory policies on user decision-making. Future studies could incorporate variables such as ecosystem competition and data privacy concerns to construct a more comprehensive behavioural explanatory framework. Additionally, with the growing adoption of multimodal large models, user interaction scenarios are becoming increasingly complex. Further exploration is needed to understand how cross-modal capabilities affect shifting behaviour, thereby offering more robust theoretical support for the evolution and application of AI technologies.

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