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Examining the Influence of Communal User Needs on Quality of Experience (QoE): The Moderating Effects of User's Purpose of Technology Use and Innovativeness

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ABSTRACT
In prior research, we defined eleven communal user needs as core elements observed across diverse technological domains, irrespective of each domain's characteristics or purposes. This research investigates how these communal user needs influence quality of experience. It also examines whether the purpose of technology use and personal innovativeness moderate this relationship, potentially shifting the relative importance of these needs. Based on a literature review, we established hypotheses and a research model. Additionally, we developed a questionnaire administered to users of generative AI and social media platforms. The model was analyzed using PLS-SEM and conducted multi-group analysis to test moderation effects. The findings show several significant effects and confirm certain moderating patterns depending on the moderators examined. Overall, this research provides cross-domain evidence from generative AI and social media platforms toward a generalizable, user-centered approach to QoE evaluation, enabling improvements in the direction that users truly want.

KEYWORDS
Quality of experience; communal user needs; partial least squares structural equation modeling

1. Introduction

With advances in artificial intelligence, natural language processing (NLP), sensors, and the Internet of Things (IoT), many intelligent systems capable of autonomously adapting and learning have been introduced (Venturini, 2022). From a human–system interaction perspective, whereas conventional systems perform tasks based on human commands, intelligent systems reshape the user experience by enabling new and diverse forms of interaction through knowledge-based actions (Dragicevic et al., 2020; Kumar et al., 2019; Zhong et al., 2017). To sustain the acceptance of these systems, a user-centered design (UCD) approach that incorporates user needs identified across diverse interactions is required. This approach ultimately leads to a positive user experience (Heo et al., 2024; Tosi, 2020).

In this context, the importance of Quality of Experience (QoE), which measures the subjective satisfaction of the user experience by encompassing the traditional, technology-centered quality metric of Quality of Service (QoS), is increasingly emphasized (Seufert et al., 2021; Shin, 2017). QoE is measured by the extent to which user needs are met, value is provided, and satisfaction is achieved during interactions with the system (Laghari & Connelly, 2012; Le Callet et al., 2013). In other words, QoE connects objective indicators of technical performance with the subjective user experience (Laghari & Connelly, 2012). Accordingly, scholars across diverse fields investigate QoE either by conducting objective evaluations (Basheer et al., 2024; Jumani et al., 2024; Laghari et al., 2020; Pierucci, 2015; Song & Tjondronegoro, 2014) or by developing theoretical models (Hameed et al., 2024; Laghari et al., 2018; Laghari, Estrela, et al., 2024; Laghari & Connelly, 2012; Minovski et al., 2020; Putri et al., 2023; Sun &

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Hines, 2022). Nevertheless, much of the current literature focuses on a narrow set of domain-specific attributes, resulting in separate QoE models for individual technological domains. Amid rapid technological change, this practice leads to the repeated construction and validation of separate models, which slows progress and reduces consistency in QoE evaluation (Heo et al., 2025). Moreover, because QoE measurement, focused on what users value and therefore inherently subjective, is not well defined, evaluations often default to technology-focused QoS (Chen & El Zarki, 2011; Kalibatienė et al., 2023).

We defined "communal user needs" in prior research to overcome these limitations (Kim et al., 2025). Although domain-specific technological characteristics lead to differences in how user needs are expressed, we identified 11 factors that users commonly perceive during technology use between intended outcomes and user needs. These communal user needs provide a foundation for describing the common structure of user experience from the user needs perspective and indicate the feasibility of a cross-domain framework for QoE evaluation that may generalize beyond individual technologies (Kim et al., 2025). Building on this foundation, it is necessary to empirically test whether each communal user need affects QoE. It is also necessary to determine how various influence factors moderate these relationships, thereby enabling a multifaceted analysis of dynamic properties such as differences in the relative importance of user needs across technologies (Sahithi et al., 2025). However, because user needs are inherently subjective, empirical studies that directly examine the relationship between user needs and QoE remain limited. Although influence factors are recognized as important in the ITU-T Recommendations that propose the concept of QoE, the literature often remains at the level of general guidance or places primary emphasis on system-related factors. Accordingly, this paper empirically analyzes how communal user needs affect QoE and investigates the moderating effects of context and human influence factors. To this end, we specify all latent variables, including QoE, as first-order reflective construct and estimate the structural model using PLS-SEM, and we present the following contributions:

- Develop and validate survey items for each element of the communal user needs.
- Using PLS-SEM across two technological domains (generative AI and social media), provide cross-domain evidence for a generalizable structure in which communal user needs influence QoE via perceived value.
- Conduct multi-group analysis based on a context influence factor (purpose of technology use) and a human influence factor (personal innovativeness) to identify moderating effects and reveal differences in the relative importance of user needs across technologies.
- Clarify the theoretical positioning by linking communal user needs with QoE theory and deriving concrete theoretical and practical implications.

The structure of this paper is as follows: Section 2 covers the basic ideas behind this research, including the key concepts of QoE, the factors that affect it, and the communal user needs identified in earlier studies. Section 3 presents the research model and hypotheses, and Section 4 explains the development of scales and data collection methods related to the research methodology. Results and discussion are presented in Section 5, and the conclusion is provided in the final section.

2. Theoretical background

2.1. Quality of experience and influence factors

As mentioned, "Firms compete on quality, customers search for quality, and markets are transformed by quality," quality is considered the most important element in business strategy while also being widespread across various fields (Golder et al., 2012). Quality is typically classified into two aspects: satisfaction with fixed specifications and satisfaction with customers (Hoyer & Hoyer, 2001; Korakianiti & Rekkas, 2011). In this regard, the International Telecommunication Union (ITU) has defined Quality of Service (QoS) and Quality of Experience (QoE), corresponding to each aspect of quality evaluation. QoS is defined as "Totality of characteristics of a telecommunications service that bear on its ability to satisfy stated and implied needs of the user of the service" (ITU-T, 1994). QoS primarily evaluates the overall performance aspects of products and services (Varela et al., 2014). However, the emphasis on technical performance in QoS reveals a limitation: it fails to adequately reflect the user experience. In fact, even if a specific system has the same level of QoS, the satisfaction levels of different users can vary (Nourikhah & Akbari, 2016). Therefore, the concept has expanded from QoS, which focuses on technical performance, to QoE, which encompasses user satisfaction. QoE was initially defined as "The degree of delight or annoyance of the user of an application or service" (ITU-T, 2006). Subsequently, the Qualinet White Paper, which comprehensively summarized QoE, redefined it as "QoE is the degree of delight or annoyance of the user of an application or service. It results from the fulfillment of his or her expectation with respect to the utility and/or enjoyment of the application or service in the light of the user's personality and current state" to provide a definition applicable to a wide range of application areas, along with the improvement of the functional refinement level of services and systems. Official adoption of this definition continues to occur today (ITU-T, 2017b; Le Callet et al., 2013).

Additionally, the Qualinet White Paper defines influence factors as "any characteristic of a user, system, service, application, or context whose actual state or setting may have an influence on the quality of experience for the user" (Le Callet et al., 2013). To establish effective QoE control, service providers must treat influence factors classified as human influence factors, system influence factors, and context influence factors (ITU-T, 2017a, 2021, 2022; Laghari, Estrela, et al., 2024; Le Callet et al., 2013). Human influence factors relate to variable and invariant human properties that shape experience. These factors can be considered at low-level and high-level processing stages of human perception. Low-level stages concern attributes related to physical, emotional, and mental states and may vary with situational conditions. High-level stages involve cognitive processing, interpretation, and judgment related to an individual's values, needs, goals, motivations, preferences, and emotions; these stages are relatively stable and do not change in the short term (Le Callet et al., 2013; Reiter et al., 2014). Nevertheless, human influence factors are highly complex and interact closely with other factors, so they should be examined from multiple perspectives (Le Callet et al., 2013). System influence factors refer to attributes that determine the technical quality of an application or service. This class of factors includes hardware, software, and configuration settings, and it is central to technology-centric service quality. Context influence factors describe the settings in which users and systems operate, including physical location, time of the experience, and the type of task performed (Reiter et al., 2014). Taken together, these definitions indicate that enhancing QoE requires considering the full set of influence factors and meeting both functional requirements and user needs.

2.2. Communal user needs

As previously defined, QoE is the result of meeting expectations regarding the usefulness and enjoyment of an application or service, and user needs are a core factor of QoE. Therefore, for user-centered QoE evaluation, it is important to conceptually understand the core factor of user needs, and furthermore, it is necessary to consider the topic from a holistic perspective by reflecting the actual user opinions that appear in various technological domains. This aligns with recent scholarship arguing that, beyond system attributes, a pluralistic perspective encompassing usage context, cultural diversity, and real user experiences is needed (Shin, 2025). To this end, we drew on international standards to clarify the relationships between user needs and related concepts and to identify 11 communal user needs across 10 technological domains (Kim et al., 2025).

Specifically, we analyzed ISO/IEC 25064:2013, ISO/IEC 25065:2019, and ISO/IEC 25066:2016—international standards on software product quality requirements and evaluation that define user needs and related concepts. As a result, we identified the relationship between user needs and their related concepts, including intended outcomes and user requirements. According to the standard, user needs are defined as "prerequisite identified as necessary for a user, or a set of users, to achieve an intended outcome, implied or stated within a specific context of use." The related concept of "intended outcome" is defined as "goal," and user requirements are defined as "set of requirements for use that provide the basis for the design and evaluation of interactive systems to meet identified user needs" (International Organization for Standardization [ISO], 2013, 2016, 2019). In summary, the intended outcome and user needs can be described as the relationship between the goals to be achieved through interaction with the system and the prerequisites for realizing them. Additionally, identified user needs can be transformed into user requirements from a technical perspective, which can be utilized in the design and evaluation processes by considering elements such as the usage context, priorities, and constraints. Depending on the usage context of each technological domain, the relationship between these three concepts manifests as domain-specific user needs and intended outcomes. However, at an abstract level, similar forms of user needs and intended outcomes can exist across different technological domains. Based on this understanding, we aimed to identify the user needs and intended outcomes that transcend each technological domain.

We selected ten heterogeneous domains by jointly considering the purpose of technology use and technological maturity and collected online reviews for each domain. The analysis integrated BERTopic with thematic analysis, and the corpus was split into (a) domain-specific datasets and (b) a merged dataset constructed by sampling an equal number of reviews from each domain. To mitigate single-algorithm bias in the merged dataset, we applied two clustering algorithms within the BERTopic pipeline (HDBSCAN and k-means clustering). After preprocessing, we extracted initial topics with BERTopic and manually merged overlapping topics, based on lexical and semantic similarity and inspection of representative reviews, to obtain the final topic model. We then conducted thematic analysis on the topic models and raw texts to define intended outcomes and user needs. For the merged dataset, we examined redundancy using topic diversity and topic similarity and then aligned the two models by semantically equivalent intended outcomes, converging on eleven global cross-domain higher-level themes. For the domain-specific datasets, we identified the intended outcomes and user needs for each domain and then mapped these onto the eleven themes to finalize both the communal intended outcomes and communal user needs. Inter-coder agreement, assessed via Krippendorff's $\alpha = 0.805$, supports the reliability and validity of the eleven communal user needs.

The final set of communal user needs and intended outcomes is presented in Table 1. In this study, communal user needs are broadly defined as the antecedent conditions that span the entire human–computer interaction process and enable users to achieve their intended outcomes. For example, the "enjoyable" aspect denotes a requirement for interactions that elicit enjoyment throughout the process and is conceptually and temporally distinct from hedonic value, which is a post-use value judgment. The "easy to control" aspect goes beyond whether a system is simply easy to use; it also considers facets such as the amount of effort invested before use through information processing, thereby distinguishing it from post hoc evaluations or general feelings captured by perceived ease of use. The "functional" aspect refers to the requirement that sufficient functionality and performance be available to achieve goals, which differs from perceived usefulness, an outcome-oriented belief about performance improvement. In short, these needs are distinguished from existing concepts in that they are not confined to post-experience appraisals such as value judgments or satisfaction but can be directly translated into concrete design and improvement decisions.

3. Research model and hypothesis development

This section presents the theoretical basis for the factors within the research model and develops research hypotheses. To this end, we develop a conceptual model explaining the relationship between user needs and QoE, based on an understanding of user needs and the definition of QoE. Specifically, as shown in Figure 1, the proposed research model and hypotheses follow a hierarchical structure comprising three stages: communal user needs, perceived hedonic and pragmatic value, and total QoE.

3.1. Perceived hedonic value, perceived pragmatic value and total QoE

The main focus of the traditional field of Human-Computer Interaction has been ensuring usability, which ISO (2023) defines as the degree to which a product or system can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use. However, due to the evolution of technology and the diversification of user needs, the concept of usability, which emphasizes practicality, is no longer sufficient to satisfy users (Hassenzahl & Tractinsky, 2006). Accordingly, user-centered product design must consider not only practical functions but also the experiential aspects of human–system interaction as a whole (Hassan & Galal-Edeen,

Table 1. Communal user needs.

Communal user needs		Intended outcome
Adaptable	The users need to be able to customize or personalize the system	In order to ensure interactions that reflect individual preferences and situational contexts
Enjoyable	The users need the beautiful appearance and an enjoyable experience	In order to experience visceral and behavioral delight
Comfortable	The users need the system designed to avoid factors that may lead to physical strain or mental stress	In order to use the system comfortably
Easy to access	The users need the system to enable a quick, effortless transition to readiness	In order to easily start interaction when needed
Easy to understand	The users need the user-friendly user interface	In order to intuitively understand the information to make efficient decisions without confusion
Easy to learn	The users need to learn how to use the system and its functions easily	In order to efficiently learn how to use the system and save time and effort
Easy to control	The users need the simple and easy way to control the system	In order to perform smooth functionality and prevent mistake
Responsive	The users need quick feedback from system	In order to enhance responsiveness and interact quickly
Consistent	The users need the system that is consistent and continuous	In order to get consistent performance over time
Resilient	The users need the system that is resilient and stable	In order to withstand external factors and maintain reliable performance
Functional	The users need the specific function and sufficient specifications	In order to achieve specific purpose effectively and accurately

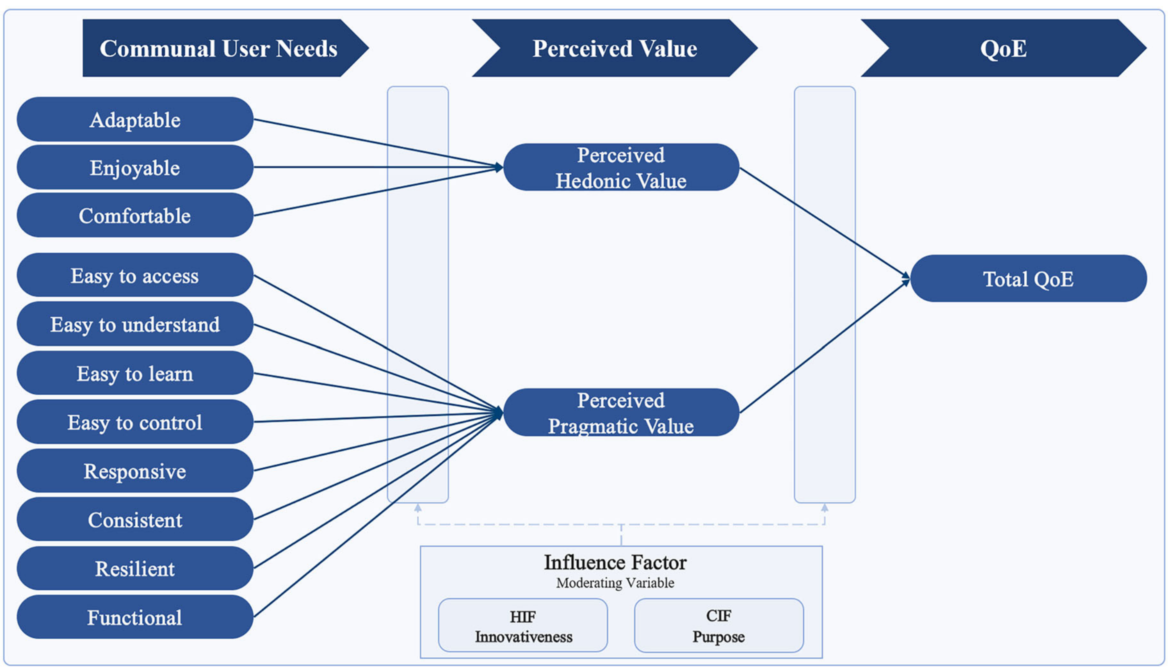

Figure 1. Research model.

2017). In this context, the concept of user experience has gained prominence. Across user experience models, the satisfaction component of traditional usability is framed as hedonic quality, whereas effectiveness and efficiency are framed as pragmatic quality (Lallemand et al., 2015). Building on this distinction, researchers have examined user experience and QoE using the hedonic and pragmatic dimensions.

Baraković and Skorin-Kapov (2017) systematically reviewed QoE research on web browsing and emphasized that both hedonic and pragmatic qualities are necessary for understanding QoE (Baraković & Skorin-Kapov, 2017). Möller et al. (2009) proposed a classification system consisting of two QoS layers and one QoE layer to address the lack of standardized evaluation metrics for multimodal conversational systems, arguing that QoE should encompass both hedonic and pragmatic components (Möller et al., 2009). Kim and Baek (2025) identified user-friendliness and playfulness of generative AI as factors shaping practical and hedonic aspects, respectively, to understand the intention for continuous use of generative AI (Kim & Baek, 2025). Laghari, Estrela, et al. (2024) argued that QoE evaluation for medical virtual and augmented reality serious games should include hedonic aspects such as fear and discomfort, presence and immersion, and game enjoyment, together with the pragmatic aspects of usability (Laghari, Estrela, et al., 2024). Based on the prior research discussed, we develop the following hypotheses:

H1. The perceived hedonic value significantly affects total QoE.

H2. The perceived pragmatic value significantly affects total QoE.

3.2. Communal user needs and perceived hedonic value

Perceived hedonic value relates to the communal user needs of the "adaptable" aspect, the "enjoyable" aspect, and the "comfortable" aspect. This is because perceived hedonic value emphasizes subjective and emotional elements such as users' pleasure and esthetic satisfaction.

Among these, the "adaptable" aspect refers to a characteristic that enables the system to adapt to individual preferences and situational context. This aspect is divided into two categories: customization and personalization. Customization refers to the process where users adjust and use the system according to their characteristics (Luo et al., 2023; Oinas-Kukkonen et al., 2022), whereas personalization involves the system's automatic provision of tailored content and services based on knowledge and information obtained through interaction with the user (Adomavicius & Tuzhilin, 2005; Oinas-Kukkonen et al., 2022). Customization induces various subjective emotional responses during the user's proactive manipulation process (Wan et al., 2017), and personalization is related to the user's emotions in that it generates positive feelings through appropriate personalized content (Pappas et al., 2012; 2014). Various studies have been conducted based on this emotional association. Jang et al. (2025) analyzed the impact of avatar-based psychotherapy in a metaverse environment on user experience and the formation of therapeutic relationships, emphasizing the importance of avatar customization as a key element of avatar self-connection (Jang et al., 2025). Kim and Lee (2020) identified the psychological mechanisms through which customization experiences affect consumer happiness and user behavior intentions, based on Self-Determination Theory (Kim & Lee, 2020). Luo et al. (2023) found that functional affordances for customization and personalization positively influence the continued use of smartwatches, with hedonic value and perceived health acting as mediators (Luo et al., 2023). Ho (2012) argues that, when examining how location-based personalization affects the intention to use mobile services, it is important to foster genuine enjoyment and interest rather than merely providing utilitarian recommendations (Ho, 2012). Pappas et al. (2014) showed that personalization elicits positive emotions, and these emotions mediate the relationship between personalization and purchase intention (Pappas et al., 2014). Thus, we propose,

H3. The "adaptable" aspect significantly affects perceived hedonic value.

Positive emotions and esthetic responses lead to positive interface interactions (Cohen, 2013; Thielsch et al., 2019). In this regard, user needs related to the enjoyable aspect, such as pleasure, fun, and esthetic satisfaction during system use, have been actively studied in relation to perceived hedonic value. Cyr et al. (2006) conducted an empirical analysis on how design esthetics influence user experience and loyalty in mobile commerce. They presented a research model that added enjoyment to the core TAM components: perceived ease of use and perceived usefulness. Their analysis indicated that esthetics had the greatest impact on enjoyment, emphasizing the need to incorporate emotional experience into design (Cyr et al., 2006).

Liu et al. (2016) used a model based on the Stimulus–Organism–Response (S-O-R) theory to analyze how website esthetic design affects users' emotions and satisfaction. The results confirmed that esthetic formality and appeal directly influence emotional experiences such as arousal and tension, which in turn contribute to user satisfaction (Liu et al., 2016). Bhandari et al. (2019) developed a model to examine how emotion and perceived visual esthetics affect users' choices of mobile apps, and their empirical analysis showed that emotion is a major antecedent of perceived quality, attractiveness, and download intention. In particular, they found that expressive esthetics, when linked to arousal, enhanced hedonic quality and increased download intention (Bhandari et al., 2019). Banik and Gao (2023) analyzed the factors influencing customer experience in a phygital retailing environment through the concept of hedonic aspects, as defined in previous research. Hedonic aspects refer to elements related to users' multisensory, fantastical, and emotional experiences, encompassing all factors that induce arousal feelings such as excitement, enjoyment, and joy. In this research, a research model was constructed focusing on mental imagery, entertainment, and esthetics to empirically verify the impact of hedonic aspects on customer experience and ultimately on decision satisfaction (Banik & Gao, 2023). In addition, prior studies have consistently shown that the esthetic and implementation qualities of interfaces, as well as the use of affective computing technologies, influence users' emotional responses (Bonnardel et al., 2011; Cyr et al., 2010; Lai et al., 2009; Lee & Choi, 2017; Makkan et al., 2020; Qiu & Benbasat, 2009). Recent work on generative AI likewise shows that hedonic motivations such as enjoyment and fun influence both acceptance of and immersion in these systems (Al-Kfairy, 2024; Lo et al., 2024). Based on this theoretical and empirical evidence, we propose the following hypotheses regarding the enjoyable aspect and perceived hedonic value:

H4. The "enjoyable" aspect significantly affects perceived hedonic value.

User needs related to the "comfortable" aspect are associated with using technology without physical or psychological discomfort. Comfort is influenced by various characteristics, including physical, physiological, and psychological factors (Slater, 1985), and is subjectively determined according to individual traits. It is also shaped by individuals' responses to stimuli (Yan & Jia, 2022). Accordingly, recent work has moved beyond physical comfort to encompass various elements. Knight and Baber (2005) proposed the Comfort Rating Scales (CRS) in the context of wearable computing; the CRS comprises six dimensions: Emotion, Attachment, Harm, Perceived Change, Movement, and Anxiety, demonstrating that comfort is a complex, multidimensional construct (Knight & Baber, 2005). Based on research by Knight and Baber (2005), Gerhardsson and Laike (2021) investigated users' perceptions and behavioral intentions regarding a personalized home lighting system utilizing wearable technology. As a result, they emphasized that measuring only acceptance and physical comfort does not adequately reflect the willingness to use, and that both psychological and physical comfort should be considered simultaneously (Gerhardsson & Laike, 2021). Vink and Hallbeck (2012) pointed out the lack of theoretical link between comfort and product design, reviewed related models, and proposed a new comfort/discomfort model. This model explains that discomfort, comfort, or the absence of sensation can result from human effects during interaction, as well as from perceived effects based on expectations. Thus, the model suggests that comfort is a multidimensional concept that includes emotions and arises from the interaction between expectations and experiences (Vink & Hallbeck, 2012). Comfort is related to an individual's subjective emotions, which is why it is considered a hedonic value in various studies. Jo (2022) defined hedonic value as "the degree to which AIPA provides pleasure, motivation, and comfort," focusing on what makes people want to keep using AI personal assistants (Jo, 2022). Kivijärvi and Pärnänen (2023) identified the components of usability and UX in the field of HCI and analyzed the interrelationships between the concepts, defining UX as consisting of instrumental enablers related to usability and quality in use that emerge during the actual usage process. In this context, it is mentioned that quality in use encompasses hedonic attributes, and comfort is selected as one of the emotion-based factors (Kivijärvi & Pärnänen, 2023). Thus, we propose:

H5. The "comfortable" aspect significantly affects perceived hedonic value.

3.3. Communal user needs and perceived pragmatic value

Pragmatic value refers to the way users utilize the practical and functional features of a system to effectively achieve specific goals. It is closely associated with usability, which facilitates ease of use; reliability, which ensures consistent and error-free operation; and functionality, which pertains to the quality of features provided by the system (Hassenzahl, 2018; Schrepp et al., 2017).

Among communal user needs related to usability, five aspects are salient: the "easy to access" aspect, which allows users to begin interacting whenever they wish; the "easy to understand" aspect, which enables users to interpret information intuitively and make decisions efficiently; the "easy to learn" aspect, which enables users to learn how to use the system efficiently, thereby saving time and effort; the "easy to control" aspect, which allows users to perform tasks smoothly and avoid errors, and the "responsive" aspect, which ensures that the system responds quickly to user actions for efficient interaction.

Several prior studies support the link between these five aspects of communal user needs and perceived pragmatic value. Shin et al. (2016) emphasized system quality as an overall attribute that enables users to use the system effectively and reliably, including components such as access, navigation, and usability, while analyzing the success factors of IT services (Shin et al., 2016). Kivijärvi and Pärnänen (2023) chose factors like learnability and operability as important enablers for pragmatic quality and analyzed how they affected mediating usability to make a satisfying user experience (Kivijärvi & Pärnänen, 2023). In their research on the acceptance of LTE services, Park and Kim (2013) analyzed how perceived mobility and perceived processing speed affected the quality of systems and services (Park & Kim, 2013). Almaiah et al. (2016) examined how quality factors affect people's willingness to use mobile learning systems. They considered various factors, including user-interface design, accessibility, availability, and responsiveness. They found that user-interface design and accessibility had the strongest effects (Almaiah et al., 2016). Thus, we hypothesize the following:

H6. The "easy to access" aspect significantly affects perceived pragmatic value.

H7. The "easy to understand" aspect significantly affects perceived pragmatic value.

H8. The "easy to learn" aspect significantly affects perceived pragmatic value.

H9. The "easy to control" aspect significantly affects perceived pragmatic value.

H10. The "responsive" aspect significantly affects perceived pragmatic value.

The "consistent" aspect and the "resilient" aspect relate to reliability for stable system use. The "consistent" aspect reflects the need for the system to operate stably for an extended period and enable continuous interaction. In this regard, users mainly emphasize that elements such as communication connections and batteries should be maintained for a long time (Alnawayseh et al., 2023; Silva et al., 2024). The "resilient" aspect pertains to the system's ability to fend off external threats and swiftly recover from failures to prevent further issues. From a software perspective, this aspect is often related to security and the reliability of information, whereas from a hardware standpoint, it typically involves the durability of the device (Al-Shafei, 2025; Bhowmik, 2024; Singh et al., 2025). Orehovački and Babić (2018) proposed a model consisting of five categories and 37 detailed attributes for evaluating the quality of social web applications on mobile devices. In the service quality category related to the interaction process, researchers considered detailed attributes related to reliability, such as "error prevention," "reliability," and "recoverability" (Orehovački & Babić, 2018). Kuo et al. (2009) structured the service quality of mobile value-added services into four dimensions and analyzed how these dimensions affect perceived value, customer satisfaction, and post-purchase intention. Based on previous research, they established "system reliability and connection quality," which refers to the quality of the system operating stably and connecting to the service quickly, as one of the four dimensions of service quality (Kuo et al., 2009). Kuo (2003) developed a measurement tool based on SERVQUAL to evaluate the service quality of virtual community websites and identified the relationship between service quality, customer satisfaction, and loyalty. The measurement tool was composed of five dimensions, including reliability, which pertains to the ability to provide the expected service accurately, consistently, and reliably, and the analysis demonstrated that reliability is a key element (Kuo, 2003). Thus, we propose:

H11. The "consistent" aspect significantly affects perceived pragmatic value.

H12. The "resilient" aspect significantly affects perceived pragmatic value.

The "functional" aspect pertains to the desire to effectively achieve goals by using the features of a given technology. It aligns with pragmatic quality, reflecting needs for functional diversity and for specific technical functions and performance beyond the general quality of technology (Quiñones et al., 2024; Renaud et al., 2019). Almaiah et al. (2016) examined factors influencing the acceptance of mobile learning and described functionality as the features that help users meet their learning goals, along with their needs for usability (Almaiah et al., 2016). Similarly, Cho et al. (2009) investigated the role of perceived user-interface design in continued usage intention within self-paced e-learning environments. In their research, functionality was defined as "the functions provided by information system that enable the user/e-learner to effectively achieve their goals" (Cho et al., 2009). Tarute et al. (2017), drawing on prior research, defined functionality as "an action that can be performed by the user" in their research of the impact of mobile app characteristics on user engagement (Tarute et al., 2017). Thus, we hypothesize the following:

H13. The "functional" aspect significantly affects perceived pragmatic value.

3.4. The moderating role of user's purpose

Various prior studies have reported that the purpose of technology use has different effects on technology acceptance. For example, Van der Heijden (2004) applied the Technology Acceptance Model (TAM) to a movie website selected as a hedonic information system that pursues user enjoyment and found that the intention to use was determined by perceived ease of use and perceived enjoyment, rather than by perceived usefulness considered in the original TAM (Van der Heijden, 2004). These findings suggest that, for systems used for hedonic purposes, enjoyment and ease of use are key factors. Moon and Kim (2001) applied an extended model that adds perceived playfulness to the existing TAM in the World Wide Web environment. They found that users with entertainment purposes were more influenced by playfulness, while users with work purposes tended to rely on usefulness. Therefore, it is necessary to consider both the hedonic and pragmatic aspects simultaneously (Moon & Kim, 2001).

Accordingly, pragmatic and hedonic purposes are recognized as key components of user experience in the context of technology acceptance (Hassenzahl, 2018; Mahlke & Thüring, 2007). Pragmatic purposes are primarily associated with do-goals, which emphasize how effectively and efficiently users can achieve specific objectives through system use (Zarour & Alharbi, 2017). In contrast, hedonic purposes correspond to be-goals, which focus on emotional satisfaction, interest, and other personal and affective experiences that arise during system interaction (Zarour & Alharbi, 2017). Given these distinctions, a user's purpose of technology use is expected to moderate the relationship between user needs and QoE. Therefore, we developed additional hypotheses to investigate the moderating effects of the user's purpose of technology use on the relationships outlined in hypotheses H1 through H13.

3.5. The moderating role of personal innovativeness

Personal innovativeness refers to an individual's tendency to adopt new systems or innovations more rapidly than others (Goldsmith & Hofacker, 1991; Rogers et al., 2014). In this context, Rogers et al. (2014) classified adopters into five categories based on their level of personal innovativeness: innovators, early adopters, early majority, late majority, and laggards (Rogers et al., 2014). Because individuals differ in their perceptions of innovation, personal innovativeness can be understood as a trait that varies across individuals (Jeong & Choi, 2022; Molinillo et al., 2023; Yang et al., 2016). Many studies have examined how personal innovativeness affects whether people accept new technology in different areas, such as voice assistants (Molinillo et al., 2023), e-commerce (Jianlin & Qi, 2010), online learning apps (Chen, 2022), and wearable devices (Jeong & Choi, 2022), because it is believed that innovative and non-innovative people behave differently when adopting new technologies. Based on this discussion, this research also established additional hypotheses regarding the moderating effect of personal innovativeness on hypotheses H1 to H13.

4. Research methodology

4.1. Instrument development

To validate the proposed research model, we designed a questionnaire. The questionnaire was created to assess communal user needs, perceived value, and total QoE, using items adopted from prior research on user experience and technology acceptance. And some items were changed or newly developed to align with the objectives of this research. Specifically, items for communal user needs were adapted based on several prior studies to ensure applicability to various technologies (Almaiah et al., 2016; Chen et al., 2021; Cho et al., 2009; Jang et al., 2016; Kivijärvi & Pärnänen, 2023; Kuo et al., 2009; Lin & Hsieh, 2016; Orehovački & Babić, 2018; Park & Kim, 2013; Sheng & Teo, 2012; Shin et al., 2016). Perceived value and total QoE were measured using newly developed items in this research.

The final questionnaire consisted of 42 items measuring communal user needs, four items measuring perceived value, and two items measuring total QoE. All items used a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), and questions regarding age, gender, and duration of technology use were also included. The overall measurement items are presented in Supplemental Appendix A.

4.2. Data collection

Data were collected via an online survey platform through September 2024, targeting Korean users who regularly use ChatGPT and Instagram, the representative platforms for each domain. The survey was administered separately for each domain, and each participant filled out a one domain survey. According to DataReportal, a global data analytics organization, 93.4% of Koreans were active social media users as of January 2024, ranking Korea sixth globally (DataReportal, 2024). In addition, the 2024 Survey on Internet Usage published by the Korean Ministry of Science and ICT indicated that the percentage of Koreans with experience using generative AI increased from 17.6% in 2021 to 33.3% in the latest survey (National Information Society Agency, 2024). These statistics support our choice of Korean users as the target sample for the two technologies examined in this research. In total, we analyzed 182 responses for social media platforms after excluding 3 invalid responses and 214 for generative AI after excluding 6 invalid responses. The respondents' demographic profiles are presented in Table 2.

To analyze the moderating effect via MGA, we divided respondents into two groups for each moderator based on the user's purpose of technology use and personal innovativeness. For the user's purpose of technology use, we dichotomized by adopting the criterion from prior work (Kim et al., 2025), which classified ten technology domains into pragmatic and hedonic purposes to derive communal user needs. Accordingly, we sampled two software contexts that primarily represent distinct purposes of use, generative AI and social media platforms. For personal innovativeness, we grouped respondents by the total score of five innovativeness-related items, following previous research that classified the top 50% (i.e., innovators, early adopters, and early majority) and the bottom 50% (i.e., late majority and laggards) as two separate groups (Jeong & Choi, 2022). Since MGA recommends roughly balanced group sizes, our sample achieved this balance. For the user's purpose of technology use, there were 214 participants in the generative AI group and 182 in the social media platforms group. Regarding personal innovativeness, within the generative AI context the upper and lower 50% groups included 112 and 102 participants, respectively, and within the social media platforms context there were 98 and 84 participants, respectively.

Table 2. The profile of the respondents.

		Generative AI		Social media platforms	
Attribute	Categories	Frequency ($N = 214$)	Percentage (%)	Frequency ($N = 182$)	Percentage (%)
Gender	Male	110	51.4	82	45.1
	Female	104	48.6	100	54.9
Age	$<$ 19 years	7	3.3	1	0.5
	19–28 years	107	50.0	76	41.8
	29–38 years	44	20.6	54	29.7
	39–48 years	33	15.4	32	17.6
	49–58 years	19	8.9	16	8.8
	$>$ 58 years	4	1.9	3	1.6
Personal Innovativeness	High PI group (the top 50%)	112	52.3	98	53.8
	Low PI group (the bottom 50%)	102	47.7	84	46.2

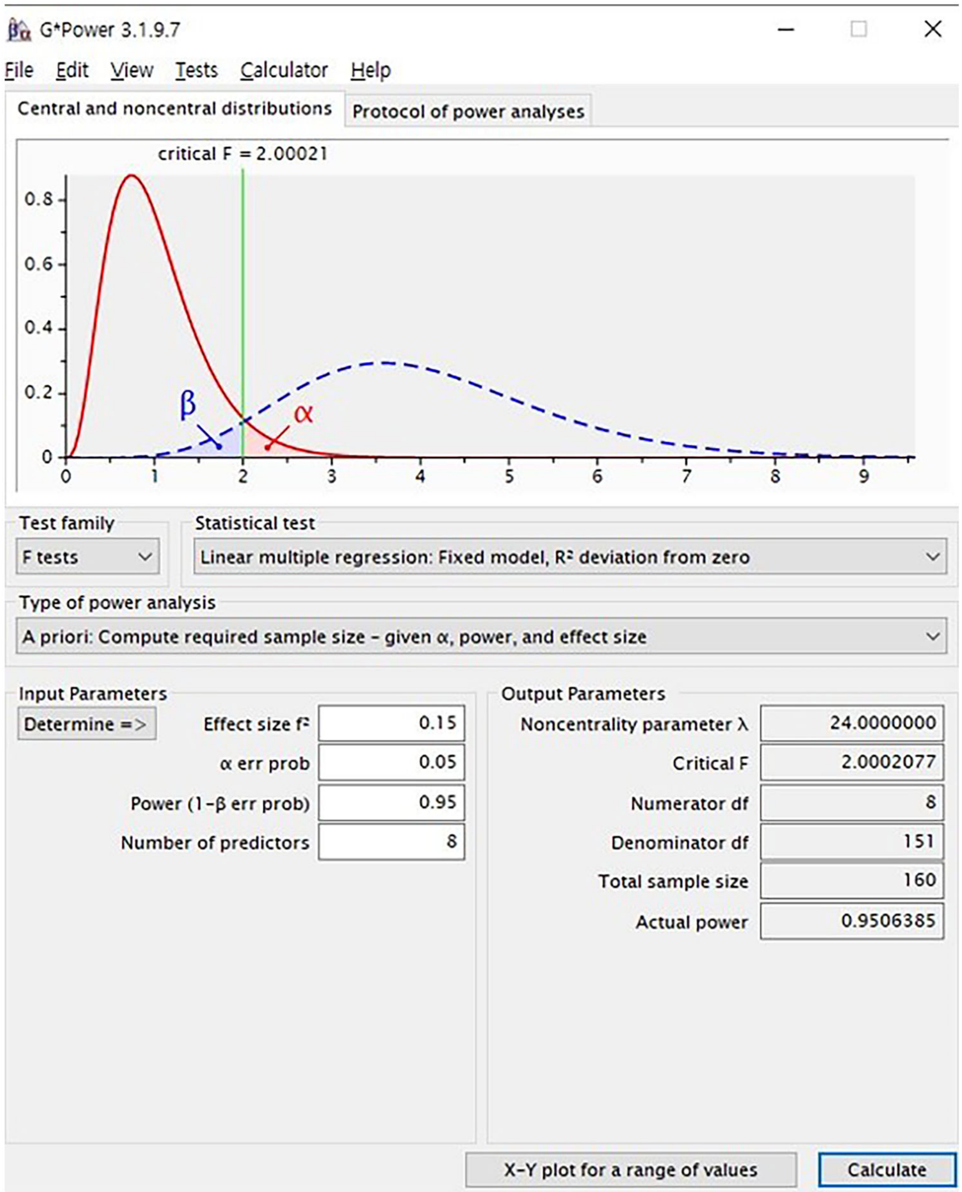

Figure 2. G*Power analysis result for determining minimum sample size.

Regarding the minimum sample size, the literature on PLS-SEM recommends G*Power analysis (Hair et al., 2022). Accordingly, we used G*Power 3.1.9.7 (Faul et al., 2007). As shown in Figure 2, we set the effect size to 0.15, the α error probability to 0.05, the power to 0.95, and the number of predictors to 8, which is the maximum number of antecedent variables for perceived pragmatic value in our model. As a result of the analysis, a total sample size of 160 was required, and since the data collected for this research far exceeded this threshold, it was confirmed that the sample size was sufficient.

5. Results and discussion

Structural Equation Modeling (SEM) is a statistical technique used to analyze complex relationships among latent constructs that cannot be directly observed (Guenther et al., 2023). We analyzed the data using partial least squares structural equation modeling (PLS-SEM), one approach within SEM. PLS-SEM was selected because the research model's conceptual framework is not entirely unidimensional; instead, it is a complex model that incorporates hierarchical structures and multiple latent variables with sequential paths, which may lead to intricate interactions among different communal user needs (Guenther et al., 2023).

Table 3. Criteria and thresholds for measurement and structural model assessment in PLS-SEM.

Criteria	Index	Threshold	
(Reflective measurement model assessment)			
Reliability	Cronbach's α	Cronbach's $\alpha \geq 0.70$	
	ρA	$\rho A \geq 0.70$	
	ρC	$\rho C \geq 0.70$	
Convergent validity	Average variance extracted (AVE)	AVE $\geq$ 0.50	
	Outer loading	Outer loading $\geq$ 0.708	
Discriminant validity	Heterotrait-Monotrait ratio (HTMT)	HTMT $<$ 0.85 (conservative cut- off value)	
		HTMT $<$ 0.90 (liberal cutoff value)	
	Fornell-Larcker criterion	$\sqrt{\text{AVE}} >$ highest correlation with other constructs	
(Structural model assessment)			
Collinearity	Variance inflation factor (VIF)	VIF $\geq$ 5	: Critical collinearity issue
		$3 \leq$ VIF $<$ 5	: Possible collinearity issue
		VIF $<$ 3	: No collinearity issue
Coefficient of determination	R^2	R^2 values $=$ 0.75 (Substantial)	
		R^2 values $=$ 0.50 (Moderate)	
		R^2 values $=$ 0.25 (Weak)	
Out-of-sample predictive power	PLSpredict	PLS-SEM shows lower RMSE than naïve linear model (LM) in the following cases:	
		None of the indicators	: No predictive power
		Minority of the indicators	: Low predictive power
		Majority of the indicators	: Medium predictive power
		All indicators	: High predictive power
Path coefficients	Significance and relevance of the path coefficients	*p*-value $<$ 0.05 or the 95% confidence interval does not include zero	

The PLS-SEM analysis was conducted using SmartPLS 4.1.1.2, following the two-stage approach recommended by Hair et al. (2021) (Hair et al., 2021). First, the measurement model was evaluated to examine the relationship between the measurement variables and the latent variables. Second, the structural model was evaluated to assess the extent to which the causal relationships proposed in the research model are supported by the data. During the assessment of the measurement model and structural model, we referenced validation indicators and criteria values from the PLS-SEM-based papers reviewed by Guenther et al. Referring to the studies by Guenther et al. (2023) and Hair and Alamer (2022), Table 3 summarizes these criteria (Guenther et al., 2023; Hair & Alamer, 2022).

Next, to examine how the purpose of technology use and personal innovativeness influenced the results, we first assessed measurement invariance using the measurement invariance of composite models (MICOM) procedure and then compared groups with multi-group permutation tests.

5.1. Common method bias

As all of this study's measures are self-reports in a single session, common method bias (CMB) could be a concern. To address it, we conducted both procedural and statistical controls and applied three remedies (Kock et al., 2021). Procedurally, we designed the questionnaire to be as clear and concise as possible, informed respondents that there were no right or wrong answers, assured confidentiality, and emphasized anonymity. Statistically, we first conducted Harman's single-factor test; the largest proportion of covariance explained by a single factor was 42.9% for generative AI and 41.2% for social media platforms, both below the 50% threshold. Second, Following Liang et al. (2007), we implemented the unmeasured latent method construct (ULMC) approach in SmartPLS. Supplemental Appendix B reports the full results. For the generative AI dataset, the average substantively explained variance of the indicators was 0.709, whereas the average method-based variance was 0.008, yielding a ratio of approximately 89:1. For the social media platforms dataset, the corresponding values were 0.751 and 0.005, respectively, yielding a ratio of approximately 150:1. Moreover, most method factor loadings were statistically non-significant. These findings indicate that CMB is unlikely to be a serious concern for our study.

5.2. Results and analysis: Assessment of measurement model

The first step in the PLS-SEM analysis was the assessment of the measurement model. Depending on the relationship between constructs and indicators, measurement models are classified as either reflective or formative. In this research, all constructs were modeled using reflective measurement models. To ensure the appropriateness of the reflective measurement model, the evaluation followed established guidelines by assessing reliability, convergent validity, and discriminant validity. The relevant indicators and threshold values for each criterion are summarized in the "Reflective Measurement Model Assessment" section of Table 3.

Reliability refers to the consistency of measurement results when the same construct is repeatedly measured using the same instrument. It was assessed using Cronbach's alpha and Dijkstra-Henseler's ρA. Although Cronbach's alpha is one of the most widely used indicators for evaluating internal consistency, it has certain limitations: it is sensitive to the number of items in a construct and assumes that all indicators share equal factor loadings (Shela et al., 2023; Werts et al., 1974). To address these limitations, Dijkstra and Henseler (2015) introduced ρA, which is currently considered the most consistent and precise estimator of construct reliability (Dijkstra & Henseler, 2015; Hair et al., 2022). The reliability assessment results are provided in Supplemental Appendix C. In the case of the Cronbach's α coefficient, generative AI ranged from 0.682 to 0.899, while social media platforms ranged from 0.742 to 0.908. There are values below 0.70 in the generative AI, but in exploratory research, values above 0.60 are considered acceptable, and since the values are close to 0.70, it was judged to be generally acceptable. For ρA, the values ranged from 0.703 to 0.901 for generative AI and from 0.749 to 0.938 for social media platforms, all values exceeded the recommended threshold. Composite reliability (ρC) follows the same threshold as ρA, and all estimates also exceeded the recommended threshold, ranging from 0.861 to 0.922 for generative AI and from 0.832 to 0.937 for social media platforms. Based on these reliability indicators, the constructs demonstrated adequate internal consistency.

Convergent validity refers to the extent to which multiple measures relate to the same idea and is assessed using average variance extracted (AVE) and indicator loadings. AVE is generally required to be above 0.50 because the construct must explain more variance than the error (Fornell & Larcker, 1981a). Similarly, indicator loading values must also be 0.708 or higher to ensure that the construct can explain more than half of the variance of the respective items. As shown in Supplemental Appendix D, AVE and indicator loadings exceeded these thresholds in both datasets, supporting convergent validity.

Discriminant validity refers to the degree to which a construct is distinct from other constructs. This was first evaluated using the Fornell–Larcker criterion, which requires that the square root of the AVE for each construct be greater than its correlations with other constructs (Fornell & Larcker, 1981b). Additionally, to improve precision in discriminant validity assessment within the PLS-SEM framework, the Heterotrait–Monotrait ratio of correlations (HTMT) was also employed (Henseler et al., 2015). As presented in Supplemental Appendix E, both generative AI and social media platforms satisfied the Fornell–Larcker criterion. Likewise, the HTMT values listed in Supplemental Appendix E were mostly below the conservative threshold of 0.90, supporting the discriminant validity of the measurement model. Along with the above two factors, the cross-loading considered when verifying discriminant validity is also categorized by domain and included in Supplemental Appendix E. All indicators loaded highest on their intended constructs, and cross-loadings on non-target constructs were markedly lower.

5.3. Results and analysis: Assessment of structural model

After completing the assessment of the measurement model, the structural model was analyzed to assess the predictive power and statistical significance of the relationships among latent variables. Following established PLS-SEM guidelines (Hair et al., 2022), we proceeded as follows. Details on the stage of evaluating the size and significance of the paths are provided in section 5.3 Results and analysis: Hypothesis Testing (Hair & Alamer, 2022; Hair & Sarstedt, 2019):

1. Examine the model for collinearity.

2. Assess the coefficient of determination (R^2).
3. Examine out-of-sample predictive power, using the PLSpredict method.
4. Evaluate the size and significance of the paths.

First, multicollinearity was examined to assess the level of correlation among constructs (Prinzler, 1974). Because high correlation can adversely affect estimation and interpretation, we assessed it before analyzing the structural model (Hair & Alamer, 2022). Multicollinearity was evaluated using Variance Inflation Factors (VIF). As shown in Supplemental Appendix F, all VIF values were below 5, indicating no multicollinearity concerns in the model.

Subsequently, the coefficient of determination (R^2) was evaluated to assess the explanatory power of the structural model. R^2 quantifies the proportion of variance in each endogenous construct explained by its exogenous predictors and reflects the in-sample predictive power of the model. R^2 ranges from 0 to 1, and the closer it is to 1, the higher the predictive accuracy is considered. R^2 varies depending on the research topic or the complexity of the model, making it difficult to present an absolute standard (Russo & Stol, 2021). Therefore, we adopted the criteria frequently used in previous research ($R^2 \geq$ 0.75: substantial, $\geq$ 0.50: moderate, $\geq$ 0.25: weak) (Hair et al., 2019). As summarized in Supplemental Appendix G, the R^2 values for QoE, PHV, and PPV were 0.658, 0.493, and 0.667 for the generative AI dataset and 0.589, 0.504, and 0.633 for the social media platforms dataset, indicating that most of the R^2 values have moderate explanatory power.

Because R^2 assesses only in-sample explanatory power, an out-of-sample predictive assessment is required to evaluate generalizability to new data (Hair et al., 2019; Shmueli et al., 2019). Therefore, PLSpredict analysis was conducted to validate the out-of-sample predictive power of the structural model. The PLSpredict analysis process involved dividing the entire data into 10 subgroups ($k = 10$) and conducting k-fold cross-validation, followed by comparing the RMSE (Root Mean Squared Error) between the PLS-SEM model and the baseline linear regression model (naïve LM). As summarized in Supplemental Appendix H, the PLS-SEM model yielded lower RMSE than the naïve model in both technology domains, supporting the model's predictive validity and its generalizability to similar contexts.

Additionally, many studies use the standardized root mean square residual (SRMR) and the normed fit index (NFI) to assess model fit. An SRMR below 0.08 and an NFI closer to 1 are generally considered indicative of good fit (Henseler et al., 2015). In this study, the SRMR was 0.065 for the generative AI model and 0.080 for the social media platforms model and the NFI were 0.702 and 0.690, respectively. These results indicate a good fit for each model.

5.4. Results and analysis: Hypothesis testing

Based on the previously established results of multicollinearity, explanatory power, and predictive performance for the structural model, the statistical significance and relevance of the path coefficients representing the hypothesized relationships among constructs were evaluated for hypothesis testing. Because PLS-SEM does not rely on normality assumptions, statistical significance is typically assessed via bootstrapping, from which *t*-values and *p*-values were obtained (Russo & Stol, 2021). Effects were assessed via standardized coefficient (β), which ranges between -1 and $+1$. We conducted a percentile-based bootstrap using 5000 bootstrap samples.

The results for the standardized coefficients, t-values, and *p*-values in the generative AI context are presented in Table 4. The analysis revealed that both perceived hedonic value and perceived pragmatic value had statistically significant positive effects on total QoE ($\beta = 0.348$, $t = 7.426$, $p < 0.001$; $\beta = 0.564$, $t = 14.010$, $p < 0.001$, respectively). For paths from communal user needs to perceived hedonic value, the "adaptable" aspect ($\beta = 0.145$, $t = 2.060$, $p = 0.039$), the "enjoyable" aspect ($\beta = 0.440$, $t = 6.203$, $p < 0.001$), and the "comfortable" aspect ($\beta = 0.201$, $t = 2.807$, $p = 0.005$) were positive and statistically significant. For paths from communal user needs to perceived pragmatic value, the "easy to access" aspect ($\beta = 0.259$, $t = 2.845$, $p = 0.004$), the "easy to understand" aspect ($\beta = 0.249$, $t = 3.326$, $p < 0.001$), the "responsive" aspect ($\beta = 0.310$, $t = 5.018$, $p < 0.001$), and the "functional" aspect ($\beta = 0.318$, $t = 4.934$, $p < 0.001$) were positive and statistically significant, whereas the "easy to learn" aspect ($\beta = -0.187$, $t = 2.312$, $p = 0.021$) was negative and statistically significant.

Table 4. Result of hypothesis testing for the generative AI domain.

Relationship			Path coefficient (β)	*t*-Statistics	*p*-Value	Hypothesis: test result	
PHV	→	QOE	0.348	7.426	0.000	H1:	Supported
PPV	→	QOE	0.564	14.010	0.000	H2:	Supported
ADA	→	PHV	0.145	2.060	0.039	H3:	Supported
ENJ	→	PHV	0.440	6.203	0.000	H4:	Supported
COM	→	PHV	0.201	2.807	0.005	H5:	Supported
EA	→	PPV	0.259	2.845	0.004	H6:	Supported
EU	→	PPV	0.249	3.326	0.001	H7:	Supported
EL	→	PPV	−0.187	2.312	0.021	H8:	Supported
EC	→	PPV	0.062	0.669	0.503	H9:	Unsupported
RSP	→	PPV	0.310	5.018	0.000	H10:	Supported
CST	→	PPV	−0.072	1.004	0.316	H11:	Unsupported
RES	→	PPV	−0.047	0.722	0.470	H12:	Unsupported
FCN	→	PPV	0.318	4.934	0.000	H13:	Supported

Table 5. Result of hypothesis testing for the social media platforms domain.

Relationship			Path coefficient (β)	*t*-statistics	*p*-value	Hypothesis: test result	
PHV	→	QOE	0.519	7.216	0.000	H1:	Supported
PPV	→	QOE	0.291	3.222	0.001	H2:	Supported
ADA	→	PHV	−0.041	0.651	0.515	H3:	Unsupported
ENJ	→	PHV	0.556	8.487	0.000	H4:	Supported
COM	→	PHV	0.237	3.631	0.000	H5:	Supported
EA	→	PPV	0.136	1.504	0.133	H6:	Unsupported
EU	→	PPV	−0.010	0.124	0.901	H7:	Unsupported
EL	→	PPV	0.079	0.973	0.331	H8:	Unsupported
EC	→	PPV	0.003	0.024	0.981	H9:	Unsupported
RSP	→	PPV	0.054	0.611	0.541	H10:	Unsupported
CST	→	PPV	−0.059	0.663	0.507	H11:	Unsupported
RES	→	PPV	0.208	2.607	0.009	H12:	Supported
FCN	→	PPV	0.509	4.928	0.000	H13:	Supported

The results for the social media platforms domain are presented in Table 5. Similar to the results in the generative AI domain, both perceived hedonic value and perceived pragmatic value had statistically significant positive effects on total QoE. For paths from communal user needs to perceived hedonic value, the "enjoyable" aspect ($\beta = 0.556$, $t = 8.487$, $p < 0.001$) and the "comfortable" aspect ($\beta = 0.237$, $t = 3.631$, $p < 0.001$) were positive and statistically significant. For paths from communal user needs to perceived pragmatic value, the "resilient" aspect ($\beta = 0.208$, $t = 2.607$, $p = 0.009$) and the "functional" aspect ($\beta = 0.509$, $t = 4.928$, $p < 0.001$) were likewise positive and statistically significant.

The R^2 values for QoE were 0.658 (generative AI) and 0.589 (social media platforms), explaining approximately 66% and 59% of the variance. Across both technological domains, the communal user needs that were significant were the "enjoyable" aspect, the "comfortable" aspect and the "functional" aspect, whereas the "easy to control" aspect and the "consistent" aspect were not significant in either case.

5.5. Results and analysis: Multi-group analysis

After testing the hypotheses for each technological domain dataset, we conducted multi-group analysis (MGA) to examine the moderating effects of the purpose of technology use and personal innovativeness. MGA assesses the significance of moderating effects by comparing differences in path coefficients between distinct groups. In particular, it provides an efficient and comprehensive analysis by evaluating the moderator's effect on all relationships within the model (Hair et al., 2010). This research conducted the analysis according to the procedures outlined by Matthews (2017) (Matthews, 2017):

1. Generate Data Groups
2. Test for Invariance
3. Analyze and Interpret Permutation Results

As noted earlier, we operationalized the purpose of technology use by forming two groups and sampling them separately: a hedonic technology group (social media platforms) and a pragmatic technology group (generative AI). Personal innovativeness was split into the top 50% and bottom 50% based on

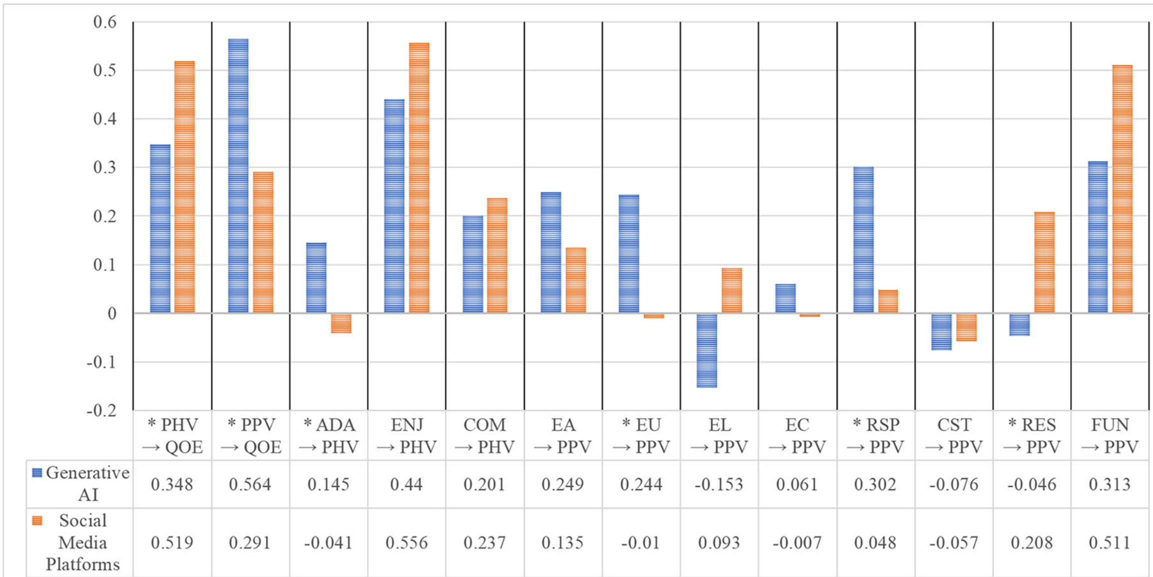

Figure 3. Comparison of standardized path coefficients between two groups by purpose of technology use.

Table 6. MGA results by purpose of technology use.

Relationship			Difference (Generative AI – Social Media Platforms)	Confidence intervals 2.5%	Confidence intervals 97.5%	Permutation p-Value
PHV	→	QOE	−0.170	−0.177	0.163	0.046
PPV	→	QOE	0.274	−0.194	0.198	0.003
ADA	→	PHV	0.186	−0.189	0.183	0.048
ENJ	→	PHV	−0.116	−0.196	0.190	0.238
COM	→	PHV	−0.036	−0.179	0.208	0.736
EA	→	PPV	0.114	−0.243	0.243	0.354
EU	→	PPV	0.254	−0.235	0.216	0.026
EL	→	PPV	−0.246	−0.245	0.252	0.051
EC	→	PPV	0.068	−0.287	0.309	0.665
RSP	→	PPV	0.254	−0.229	0.236	0.034
CST	→	PPV	−0.019	−0.235	0.252	0.883
RES	→	PPV	−0.254	−0.245	0.225	0.029
FCN	→	PPV	−0.198	−0.284	0.277	0.175

the total scores of the innovativeness-related survey items, categorizing them into the high and low personal innovativeness groups, respectively. Subsequently, the measurement homogeneity, which is a prerequisite for multi-group analysis, was verified. If measurement invariance is not met, it is impossible to distinguish whether the cause of the differences is due to group differences or individual differences (Kline, 2023). MICOM sequentially verifies configural invariance, compositional invariance, and the equality of composite mean values and variances. First, configural invariance means that the same variables should be measured with the same definitions and methods across all groups (Henseler et al., 2016). Configural invariance is the stage where it is verified whether the variables are formed in the same way across groups, based on permutation tests. Equality of composite mean values and variances is assessed for consistency across groups, and similarly, it is verified through permutation tests. When MICOM steps 1 and 2 are satisfied, partial measurement invariance is established and multi-group analysis is possible. All multi-group analyses in this research were confirmed to have achieved partial measurement invariance by passing MICOM steps 1 and 2, as summarized in the results in Supplemental Appendix I.

After the MICOM analysis, we analyzed moderating effects based on the purpose of technology use. Specifically, we compared the groups of generative AI platforms and social media platforms. The visualization of standardized path coefficients across the two domain groups is presented in Figure 3, and the MGA results are summarized in Table 6. The analysis revealed significant differences in how perceived hedonic value and perceived pragmatic value affect QoE by purpose of technology use.

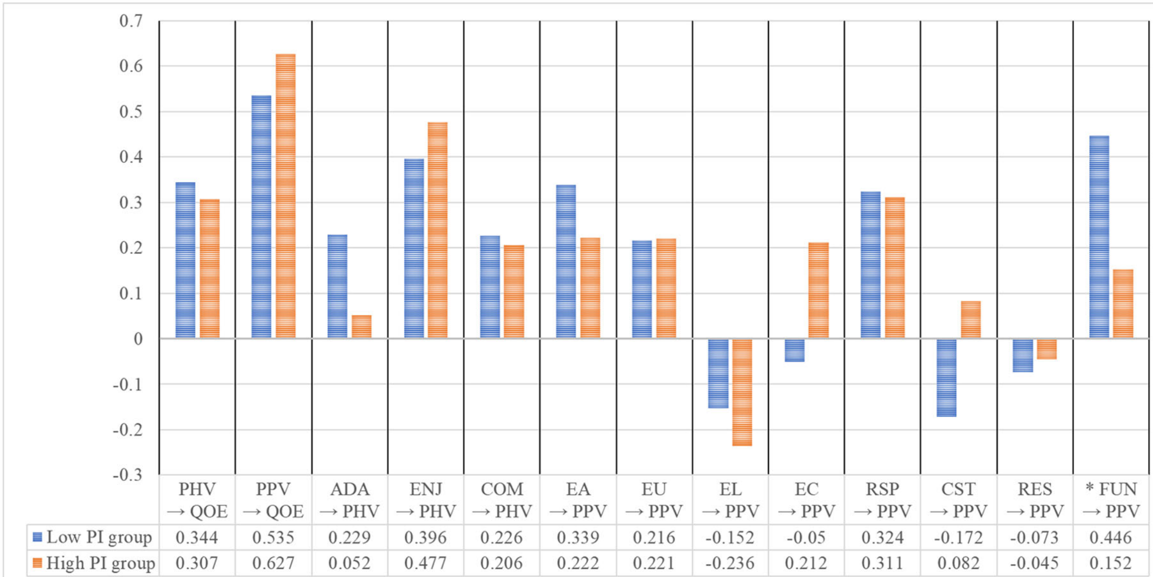

Figure 4. Comparison of standardized path coefficients between two groups by innovativeness (generative AI).

Table 7. MGA results by personal innovativeness in the generative AI domain.

Relationship			Difference (Low PI group − High PI group)	Confidence intervals 2.5%	Confidence intervals 97.5%	Permutation p-Value
PHV	→	QOE	0.037	−0.183	0.192	0.711
PPV	→	QOE	−0.092	−0.161	0.173	0.288
ADA	→	PHV	0.177	−0.274	0.274	0.219
ENJ	→	PHV	−0.082	−0.284	0.269	0.602
COM	→	PHV	0.020	−0.301	0.281	0.889
EA	→	PPV	0.116	−0.351	0.351	0.553
EU	→	PPV	−0.005	−0.300	0.288	0.977
EL	→	PPV	0.084	−0.322	0.318	0.622
EC	→	PPV	−0.262	−0.387	0.357	0.198
RSP	→	PPV	0.013	−0.244	0.255	0.934
CST	→	PPV	−0.254	−0.291	0.308	0.088
RES	→	PPV	−0.029	−0.275	0.246	0.846
FCN	→	PPV	0.293	−0.249	0.274	0.024

Generative AI users placed greater weight on perceived pragmatic value, while social media platforms users placed greater weight on perceived hedonic value. In terms of communal user needs, statistically significant differences in perception between the two groups were observed for certain elements. Generative AI users rated the elements of the "adaptable" aspect, the "easy to understand" aspect, and the "responsive" aspect higher than social media platforms users, while social media platforms users rated the "resilient" aspect higher than generative AI users. Based on this analysis, paths showing significant differences were marked with an asterisk (*) in front of the path label in the data table of Figure 3 so that these differences can also be readily identified visually.

Next, to verify the moderating effect of personal innovativeness, we compared the differences between the lower and upper subgroups of personal innovativeness within user groups of each technology. For generative AI, the visualization of standardized path coefficients across the two groups is presented in Figure 4, and the MGA results are summarized in Table 7. For social media platforms, the visualized path coefficients are presented in Figure 5, and the MGA results are summarized in Table 8. Personal innovativeness had a moderating effect in the generative AI context on the relationship between the "functional" aspect and perceived pragmatic value, and this effect was stronger in the lower group than in the higher group of personal innovativeness. In the case of social media platforms, no statistically significant moderating effect was detected.

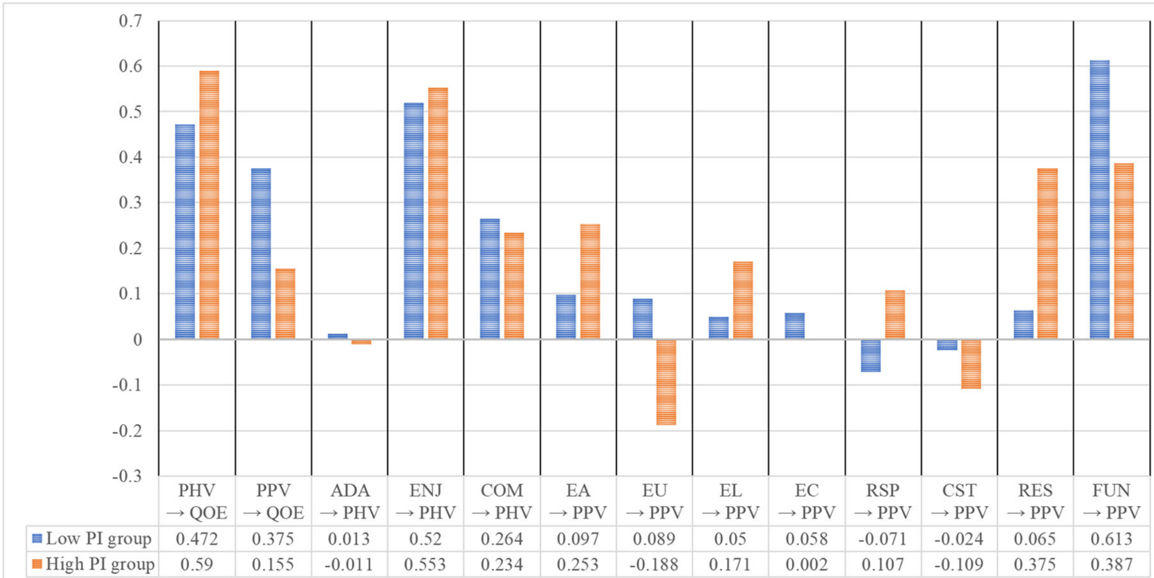

Figure 5. Comparison of standardized path coefficients between two groups by innovativeness (social media platforms).

Table 8. MGA results by personal innovativeness in the social media platforms domain.

Relationship			Difference (Low PI group − High PI group)	Confidence intervals		Permutation
				2.5%	97.5%	*p-value*
PHV	→	QOE	−0.118	−0.304	0.307	0.444
PPV	→	QOE	0.220	−0.344	0.372	0.263
ADA	→	PHV	0.024	−0.240	0.252	0.843
ENJ	→	PHV	−0.033	−0.262	0.260	0.802
COM	→	PHV	0.030	−0.249	0.262	0.809
EA	→	PPV	−0.156	−0.359	0.368	0.409
EU	→	PPV	0.277	−0.291	0.285	0.062
EL	→	PPV	−0.121	−0.351	0.329	0.535
EC	→	PPV	0.056	−0.443	0.452	0.803
RSP	→	PPV	−0.178	−0.350	0.373	0.353
CST	→	PPV	0.085	−0.350	0.346	0.635
RES	→	PPV	−0.310	−0.344	0.326	0.066
FCN	→	PPV	0.225	−0.428	0.423	0.320

5.6. Discussion

This research empirically examined the impact of 11 communal user needs, commonly perceived across diverse technological domains, on QoE and explored the moderating effects of the purpose of technology use and personal innovativeness. First, PLS-SEM was employed to test the structural relationships between communal user needs and QoE, followed by multi-group analysis to assess the moderating effects. Based on the findings, this research proposes a communal user needs-driven framework for QoE evaluation and highlights the value of a UCD approach that may be more efficient than traditional domain-specific, function-based evaluation methods. This section discusses the theoretical and practical implications, as well as limitations and directions for future research arising from the findings of this research.

5.6.1. Theoretical implications

This research empirically elucidates the relationship between 11 communal user needs identified in prior research and QoE and yields several theoretical implications.

First, this research verifies that various user needs influence QoE via perceived value, thereby extending the theoretical foundation. Across both technological domains examined, communal user needs had statistically significant positive effects on QoE through perceived hedonic value and perceived pragmatic value. These results support the existing research trend of considering both hedonic and pragmatic aspects, as previous studies related to UX and HCI have emphasized the importance of overall user experience beyond merely ensuring usability to achieve user goals (Baraković & Skorin-Kapov, 2017; Kim & Baek, 2025; Möller et al., 2009). Effects linked to perceived pragmatic value were stronger for generative AI, whereas effects linked to perceived hedonic value were more pronounced for social media platforms. This finding suggests that the manifestation of user needs varies by the purpose of technology use, and these differences are directly reflected in how QoE is formed. This theoretical extension regarding communal user needs further emphasizes the importance of user needs in QoE evaluation.

Second, this research suggests a way to improve existing QoE models, which have predominantly focused on technical specifications, by placing user needs at the center and modeling influence factors such as personal innovativeness and purpose of technology use as moderators. Several QoE-related ITU-T recommendations advise considering human, system, and context influence factors at a macro level (ITU-T, 2017a, 2021, 2022; Le Callet et al., 2013). However, in practice, most QoE modeling efforts remain heavily centered on system influence factors, such as technical specifications, while human and context influence factors are often insufficiently addressed. Prior studies on generative AI (Du et al., 2024; Huang et al., 2024; Liu et al., 2024) and social media platforms (Laghari, Zhang, et al., 2024; Wang et al., 2013), which are the focus of the technological domains of this research, also tend to concentrate on quality of service (QoS) in efforts to enhance QoE. In response, we propose a revised model that centers user needs and systematically integrates related system influence factors while treating personal innovativeness as a human influence factor and the purpose of technology use as a context influence factor. This approach enables a more nuanced and comprehensive assessment of QoE than traditional models that are primarily driven by technical specifications.

Third, communal user needs apply to a wide range of technological domains, and the differences in their relative importance depend on various influence factors. In the moderation analysis by purpose of technology use, it was found that generative AI is strongly influenced by perceived pragmatic value, while social media platforms are strongly influenced by perceived hedonic value, and this difference was statistically significant. Specifically, when using pragmatic technologies, users tend to prioritize needs such as rapid system feedback and intuitive interfaces, which reflect their goal-oriented usage patterns (Blinda et al., 2019; Collier et al., 2014; Prebensen & Rosengren, 2016). In contrast, hedonic technologies are used in a more process-oriented manner, where users value emotional experiences such as fun, enjoyment, and esthetic satisfaction (Blinda et al., 2019; Collier et al., 2014; Dhar & Wertenbroch, 2000). These differences in the nature of technology use contribute to the variation in the relative importance of communal user needs across technological domains. With respect to personal innovativeness, although only one path showed statistical significance, a general tendency toward differences in relative importance was observed. For generative AI, the relationship between the "functional" aspect and perceived pragmatic value was significantly stronger in the low-innovativeness group. A similar, albeit statistically non-significant, trend was found for social media platforms. This suggests that less innovative users tend to prefer familiar usage patterns over exploring new functionalities (Yi et al., 2006) and therefore assign greater importance to basic functional needs required for operating the technology smoothly and reliably. By contrast, although not statistically significant, highly innovative users showed a tendency to prioritize perceived pragmatic value in pragmatic contexts and perceived hedonic value in hedonic contexts more than their less innovative counterparts. Given that personal innovativeness reflects users' willingness to accept and learn about innovations (Goldsmith & Hofacker, 1991), such users are more likely to be motivated to explore new technologies, leading to a more profound understanding of their intended purposes. These findings demonstrate the value of assessing the relative importance of user needs by context and human influence factors. Doing so helps identify the most critical needs perceived by users and provides practical guidance for enhancing QoE. Since relative importance offers a basis for prioritizing user needs in the design and refinement process, it is necessary to account for diverse influence factors when evaluating and applying these priorities.

5.6.2. Practical implications

The practical implications of this research are as follows. First, the 11 communal user needs identified in this research can serve as concrete design guidelines for implementing UCD. UCD is an iterative design process that focuses on users and their needs at every stage of development. Because UCD emphasizes understanding and addressing user needs across all phases of product development and refinement, the timely identification and fulfillment of those needs are critical. The 11 communal user needs proposed in this research can be linked to technical specifications to assess whether key user needs are being addressed during the early planning and conceptualization stages. Furthermore, they can help identify gaps and areas for improvement. Because these communal user needs were derived from online user reviews across multiple technological domains, their incorporation into the UCD process is likely to approximate the effect of directly applying real user feedback. As such, these needs are expected to provide a valuable reference point for evaluating and improving the QoE in future design efforts across various technological contexts.

Second, the findings emphasize the need for design strategies tailored to the intended purpose of technology use, with priorities set according to how communal user needs manifest. Among the eleven communal user needs, examining the manifestation patterns of those related to perceived hedonic value, both the "enjoyable" aspect and the "comfortable" aspect were strongly linked in both technology areas, while the "adaptable" aspect was only important in the generative AI domain. The "adaptable" aspect tends to trigger positive emotions after using the personalization and customization features built into the system. On the other hand, the "enjoyable" aspect and the "comfortable" aspect are more directly tied to immediate emotional satisfaction. Given that the primary goal of hedonic technologies is to generate positive emotional experiences during use, the "adaptable" aspect appears to be relatively less central than the other two in hedonic contexts. Regarding perceived pragmatic value, the "functional" aspect showed a strong association in both domains, likely because functionality constitutes a basic need across technologies. Moreover, in the generative AI, users valued the "easy to access" aspect, the "easy to understand" aspect and the "responsive" aspect. In contrast, users of social media platforms valued the "resilient" aspect. These findings suggest that users of pragmatic technologies prioritize usability for achieving their goals, whereas users of hedonic technologies demand a stable environment free from elements that disrupt emotional satisfaction, such as hacking and negative users. Additionally, an intriguing result was observed in the "easy to learn" aspect of generative AI. Although most users reported that the system was able to learn how to use it easily, this aspect showed a significant negative relationship with perceived pragmatic value. This finding suggests that even if learning and getting accustomed to the system is easy, users may still perceive it as less practical if the quality or reliability of the information provided is insufficient to support goal achievement (Shin, 2025).

Given that the manifestations of communal user needs differ by domain, a priority-based design strategy is required. For example, the path coefficients for the "enjoyable" aspect and the "functional" aspect are 0.440 and 0.318 in the generative AI and 0.556 and 0.509 in the social media platforms, respectively, which are the largest effects in both domains. Accordingly, these two aspects can be regarded as the needs that users prioritize most, in affective and functional terms, regardless of domain. Issues related to them should therefore be addressed first. The next step is to specify design directions based on domain-specific user needs. In the generative AI, the "responsive" aspect ($\beta = 0.310$), the "easy to access" aspect ($\beta = 0.259$), and the "easy to understand" aspect ($\beta = 0.249$) are especially salient. Thus, the design should focus on minimizing latency, providing intuitive information architecture and terminology, and reducing onboarding friction. In contrast, for social media platforms, the "comfortable" aspect ($\beta = 0.237$) and the "resilient" aspect ($\beta = 0.208$) are relatively more important. Hence, the design should prioritize reducing the frequency of intrusive elements such as ads and notifications to ensure long-session comfort and strengthening account-level security measures. Finally, even if some communal user needs exhibit only modest effects, this may simply reflect that the corresponding domain-specific user needs have lower priority at a given time or in a given context. It does not mean those communal user needs are absent. Continuous checks are therefore necessary to determine whether such needs are manifesting through other forms of domain-specific user needs. In sum, even the same communal user needs can manifest differently depending on the purpose of technology use, and the relevant technical specifications and domain-specific user needs can vary by technological domain. Therefore, design strategies should be developed with these contextual differences in mind.

Lastly, this research presents cross-domain evidence for a generalizable, communal user needs-based approach to evaluating QoE, which is currently conducted based on different technical specifications across various technological domains. If user-centered QoE evaluations are conducted based on this model, it is expected that not only will comparative evaluations with other technologies become possible, but also improvements can be made in the direction that users truly desire.

5.6.3. Limitations and directions for future research

Despite its theoretical and practical contributions, this research has several limitations. First, the analysis is based on survey responses from users of generative AI and social media platforms, and the sample was drawn from a single cultural context; accordingly, the findings are likely to reflect characteristics specific to those technology domains and that culture. We plan to extend validation beyond the two domains and cultural settings examined here by conducting continued sampling across diverse contexts. Second, it is difficult to determine whether certain communal user needs that showed no statistically significant effects were perceived as basic expectations and therefore exhibited low relative importance, or whether the lack of significance stemmed from domain-specific characteristics. Future studies should further investigate the relative importance of each user need by integrating the proposed universal model framework with the Kano model. Third, all constructs were measured via self-report, which may bias estimates or undermine validity. To address this, future studies should collect data in real-use contexts or track QoE using behavioral data to triangulate with self-reports. Fourth, because all constructs were measured at a single point, the cross-sectional design limits strong causal inference. Longitudinal designs are therefore needed to establish temporal precedence and strengthen internal validity. In addition, research is needed to systematically link specific communal user needs to technical specifications in order to guide improvements that align with users' actual expectations.

6. Conclusion

This research empirically examined how communal user needs, mediated by perceived hedonic and pragmatic value, affect QoE. The findings indicate that communal user needs are applicable across heterogeneous technologies, although their relative importance may vary with context and human influence factors. Taken together, these results provide cross-domain evidence toward a generalizable evaluation approach that flexibly adjusts the relative importance of communal user needs to the evaluation context and target technology, thereby accommodating diverse influence factors.

Author contributions

CRediT: **Beom-Su Kim**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft; **Sang-Ho Kim**: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Ethical approval

All participants agreed to the informed consent before participation. Privacy and confidentiality were completely protected; no identifiers or personal information was collected or stored, including the participant's name, IDs, and others. This study was approved by the institutional review board (IRB) of Kumoh National Institute of Technology (No. 202110-HR-016-03).

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Data availability statement

The data that support the findings of this study are available from the corresponding author (D.A.) on request.

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