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The emotional interaction from the perspective of human-machine communication: The case study of intelligent home products

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Abstract: This study uses a mixed-methods approach that combines factor analysis with expert interviews to explore the key factors shaping human-machine interaction in intelligent home environments, particularly within the emerging metaverse context. Fifteen significant factors were identified and classified into two categories: design-optimizable factors such as emotional engagement, adaptability, and usability, and user-centric factors like personality traits, behavioral habits, and regulatory constraints. Emotional and feeling-oriented elements, including trust, fun, and surprise, emerged slightly more influential than efficiency-driven factors like information accuracy and systematization. Expert insights highlighted the critical role of social influences, such as peer endorsement and interaction atmosphere, especially in enhancing emotional acceptance among children. The novelty of this study lies in its integration of metaverse-driven scenarios and visual interaction mapping to analyze both positive and negative drivers of user engagement across physical, virtual, and hybrid spaces. Based on these findings, the study recommends a development path of "entity-based, hybrid-led, virtual-supplemented" design supported by AR and environmental sensing technologies, alongside emotionally resonant features and greater user control over data and system intelligence to enhance privacy, satisfaction, and overall emotional comfort in smart home interactions.
Keywords: *Emotional design, Human-machine interaction, Metaverse, Smart home design, User experience.*

1. Introduction

The rise of AI technologies is reshaping daily life, much like the shift brought about by smartphones [1]. Users must now adapt to new contexts of product use driven by AI. Human-machine communication, particularly emotional interaction, will be key in helping people and machines build familiarity, collaborate, and form emotional connections [2]. Unlike traditional electronic products, intelligent devices now go beyond following instructions to making decisions and providing feedback through machine learning and enhanced autonomy [3]. This study explores the emotional interaction design of intelligent home products within the framework of human-machine communication. It proposes a model of emotional interaction design, developed through a mixed-method approach combining qualitative and quantitative research, to guide future design and development in intelligent home products [4]. As the world's largest manufacturing country, China has a complete industrial system that produces over 220 industrial products, maintaining a dominant role in the global industrial supply chain [5]. In 2022, China's industrial value-added grew by 3.6%, with manufacturing contributing 33.5 trillion yuan, making it the largest in the world. This strong industrial foundation supports China's "factory of the world" status and reinforces its material base for modernization. The Chinese Government aims to leverage technological advancements to enhance global development. As a central manufacturing hub, China's focus on developing high-quality intelligent products that meet market demands is vital.

Shanghai, China's largest city, is key in high-tech manufacturing. In June 2022, the Shanghai Action Program for Promoting Intelligent Terminal Industry Development (2022-2025) was introduced to

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establish a leading household brand of intelligent terminals [6]. The study of emotional interaction design for intelligent products in Shanghai is significant for guiding product design in China and globally.

While current household intelligent products prioritize functionality and efficiency, consumers also have complex emotional needs. Users' emotional experiences with these products significantly impact satisfaction [7]. Emotional interaction design is crucial for enhancing user experience with intelligent products. These products, defined as Internet-connected devices that use AI for intelligent communication, offer new opportunities for research in communication science, focusing on how AI enables "human-machine" interactions through autonomous learning [8].

Human-machine communication continues to evolve with advancements in technology and ideas. It began with the rise of computer technology and has progressed with the development of the Internet of Things (IoT) and artificial intelligence (AI), with machine learning now at the forefront of human-machine interactions [3].

This study focuses on intelligent home products for several reasons: they are widely used in domestic settings, have mature applications, and offer ample research opportunities. Additionally, their emotional characteristics are more pronounced, as users tend to select products they enjoy in the comfort of their homes, making emotional interaction research more effective. Finally, the home environment is a personal space, providing a unique context for studying user interactions, intelligent products, and physical and virtual spaces. This study aims to propose and validate a "hybrid communication model of intelligent products" to explore new trends in intelligent communication driven by technological advancements [8].

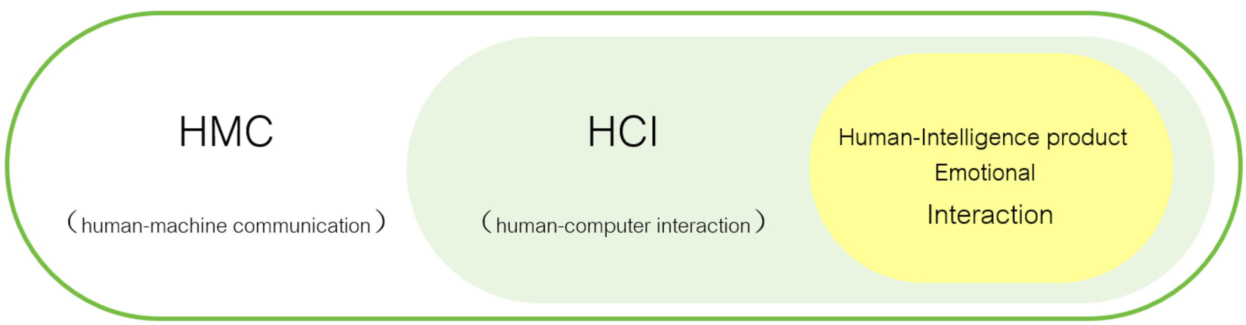

Figure 1.
Inclusive Relationships in Human-Machine Communication.

The role of machines in human-machine communication has shifted with the advent of the Internet of Things (IoT) and artificial intelligence (AI), transforming them from mere communication mediums to active participants in the communication process [1]. AI products now serve as communication mediums, second-hand communicators that filter and process data, or even as e-audiences, learning from both external and user data to serve future needs better. This study focuses on the changes, opportunities, and challenges this evolving communication dynamic poses. Its ultimate aim is to design intelligent products that are more efficient, considerate, and aligned with new communication contexts, enhancing both user experience and communication effectiveness.

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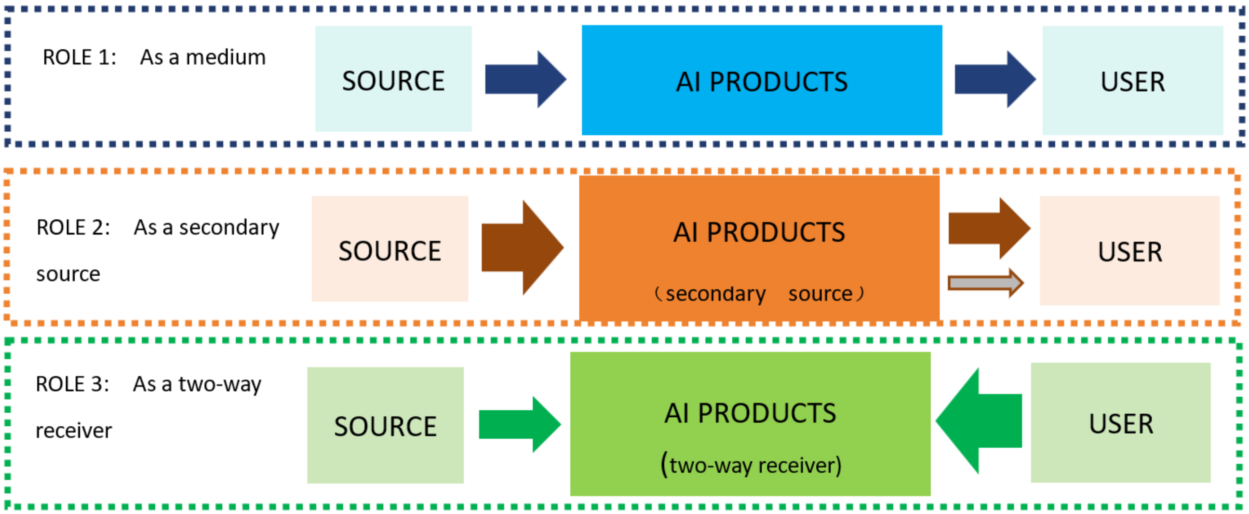

Figure 2.
Three communication roles for intelligent products.

This empirical study will explore the following questions: What are the similarities, differences, and developments between the emerging human-machine and traditional communication models? What factors influence the emotional interaction of intelligent home products? How do these factors play a role in various human-machine communication contexts?

The objectives of the study are to examine how the human-computer communication model has evolved from the traditional communication model and its Impact on the future of communication, to identify the factors influencing emotional interaction with intelligent home products in emerging communication contexts, and to develop emotional interaction design strategies for intelligent home products.

This study proposes the *Mixed Context Communication Model of Intelligent Products* to explore emerging trends in intelligent communication driven by technological advancements. The model conceptualizes each intelligent product as an active communication subject capable of interacting across real and virtual spaces, dynamically adapting to varying contexts and communication focuses [8]. The research analyzes emotional interactions between users and intelligent products in diverse communication settings.

Focusing on intelligent home products in Shanghai, China, an innovation hub, the study engages household users, industry practitioners, senior users, and experts from 2022 to 2025. Its interdisciplinary scope spans communication, design, computer science, psychology, and sociology, addressing a notable gap in the existing literature and creating opportunities for new theoretical development [2, 4]). By examining emotional interaction design within real-world and metaverse environments, the study advances the field of human-machine communication. Its findings will inform AI product development by clarifying user needs and validating emotional design strategies, ultimately offering actionable guidelines for designing intelligent home products that enhance user experience [7].

2. Literature Review

2.1. Technology Determinism

This study is grounded in technological determinism, which suggests that technology drives historical and societal changes, influencing social, political, economic, and cultural shifts [9]. Further, it argued that the significance of media lies not in the content it conveys but in how technological factors within media reshape work processes, life pace, and ultimately social structures [10]. As human-computer interaction evolves through technological advancements, it alters how people interact, think, and perceive social structures.

As new interaction scenarios emerge, traditional methods and content are no longer sufficient to meet contemporary needs. Technological determinism emphasizes updating communication concepts and finding new models aligning with technological progress and social development. Further, it is argued that changes in communication technologies are not merely human choices but inevitable outcomes of technological advancements [11]. Viewing media as an extension of human perception offers valuable insights into this study, where, in the context of home environments, the interaction between users and intelligent home products can be seen as a form of intrapersonal communication, facilitating self-regulation and balance. The study proposes "The Mixed Context Communication Model of Intelligent Products," focusing on emotional interactions with intelligent products in the home setting.

2.2. Digital Utopia & Metaverse

At the end of the 20th century, the rapid development of computer technology and the internet gave rise to new social concepts, such as information, networks, and electronic utopias. Negroponte's *Digital Survival* predicted that the "intelligent age," once considered science fiction, has primarily become a reality in the 21st century. Today, interconnected digital existence is a fundamental aspect of our world [12].

Initially, digital utopia represented the hope of breaking media hegemony through new technologies, with many believing that these advancements would lead to a world of greater freedom, democracy, and equality (Severin & Tankard, 2013). However, scholars have gained more profound insights into these concepts as society evolves. In *The Story of Utopia*, Lewis Mumford categorized utopian ideals into "utopia of escape," which detaches people from reality, and "utopia of reconstruction," which aims to improve the real world through positive transformation.

The metaverse, a new concept emerging in recent years, aims to create an open, equal, and free virtual world parallel to the real one, aligning closely with the dream of a digital utopia. This study focuses on how the metaverse, utilizing the internet and virtual reality technologies, can overcome time and space limitations to enhance human-machine communication and improve user emotional experiences. Some researchers argue that with its decentralized, interconnected, and collaborative nature, digital society should build a virtual world based on efficiency, intelligence, interaction, and sharing [12]. The metaverse, powered by virtual and extended reality technologies, holds the potential to create a new world full of limitless possibilities.

2.3. Gatekeeper

Many researchers continue to express concern that while the ideal of a Digital Utopia is appealing, the reality of an unequal "digital divide" persists, and the varied participation of individuals online can lead to irrational phenomena, such as online violence. It raises the question: Does a digital utopia characterized by absolute equality, freedom, and democracy truly exist, or is it merely a beautiful fantasy? Even in a virtual digital world, information gatekeepers are essential.

Bass [13] highlighted that while numerous checkpoints exist in the process of information dissemination, the most crucial gatekeeper is the media [14]. In today's rapidly evolving communication landscape, the role and perceptions of these 'gatekeepers' responsible for controlling the flow of information have shifted. The increasing digitization of communication prompts the need to reconsider the functions of these gatekeepers and how their influence affects the dissemination of information in both virtual and real worlds.

2.4. Field Theory

Schramm [15] praised the four pioneers of communication studies, including Lewin [16] a renowned experimental psychologist known for his work using experimental methods. Much of the research in this study draws on Lewin's *Field Theory*, which serves as a key theoretical foundation for the proposed hypothesis.

Lewin's *Field Theory* focuses on studying individuals within their "field", an environment where events are influenced by the strength of various elements in an individual's current surroundings [17]. The core idea of this theory is that behaviour is a function of both the person and their environment (B = f(P, E)), emphasizing the dynamic interaction between psychological factors and the environment. In the home context, intelligent products represent significant environmental factors, and the interaction within an intelligent home system can profoundly affect the user's psychology and experience.

Another critical aspect of *Field Theory* is that everything operates under opposing forces in equilibrium. The force driving change is called the "driving force," while the opposing force that seeks to maintain the current state is the "restraining force." Lewin [16] argued that for a system to change, the driving force must overcome the restraining force, disrupting the balance. His well-known *Force Field Analysis* diagram illustrates this concept.

In this study, Lewin's *Force Field Analysis* will be applied to explore the interactions among the three key elements in the "human-machine-environment" communication system. This improved version of the analysis chart will serve as a tool to investigate user needs and emotional responses, providing a structured framework to understand how these factors interact and influence the user's experience with intelligent home products.

2.5. Conceptual Framework

In developing emotional interaction design strategies for smart home products, the study draws on two key theoretical foundations: the "Use and Satisfaction" Theory and the Cultivation Theory. These theories will guide the understanding of user behaviour and satisfaction, offering valuable insights into how users interact emotionally with smart home technology. The "Use and Satisfaction" Theory posits that users engage with technology to fulfil specific needs, and their level of satisfaction is directly tied to how well the technology meets those needs. This theory helps to frame emotional responses to smart home products based on their effectiveness and alignment with user expectations. Cultivation Theory, on the other hand, focuses on the long-term effects of media and technology on users' perceptions and attitudes. This theory will help understand how continuous exposure to smart home products might influence users' emotional connections, perceptions of control, and overall satisfaction.

Together, these theories form the foundation for designing emotional interaction strategies that enhance the user experience with smart home products. These strategies ensure that the products meet functional needs and foster positive emotional engagement. As illustrated in Fig. 3, the research framework outlines each stage's primary data sources and methods.

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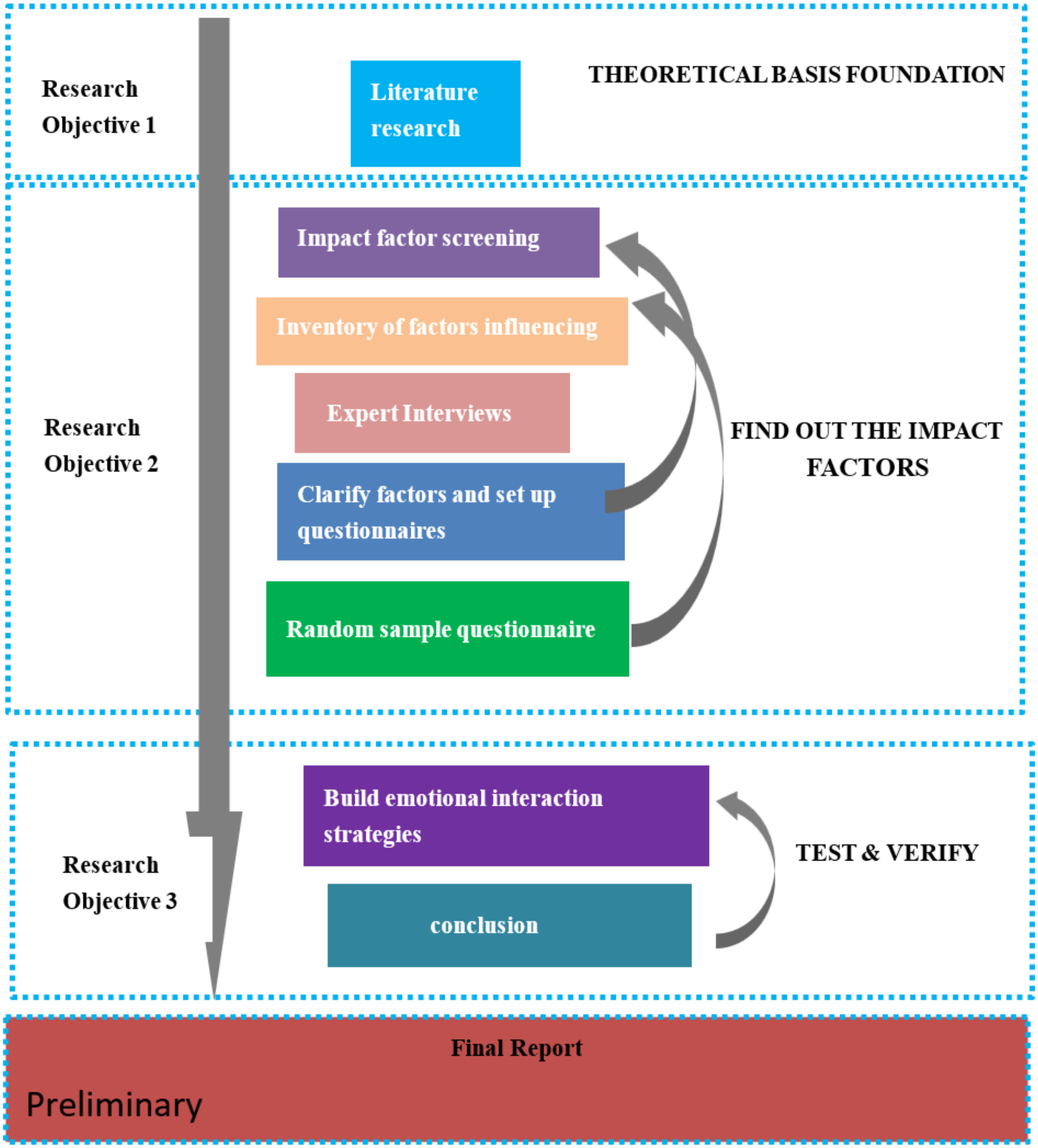

Figure 3.
Conceptual Framework.

3. Methodology

3.1. Populations and Sampling

This study explores the emerging field of intelligent communication, focusing on the Shanghai region, one of China's leading innovation hubs for innovative products with a diverse and open market.

Shanghai's broad range of modern household types makes it an ideal research setting. Based on ordinary home users, the study surveyed 400 households to assess user-product communication, attitudes, and expectations for future human-machine interaction.

In addition to home users, the study engaged industry professionals involved in designing, producing, and selling intelligent products, along with experienced users and experts. Their insights gathered through in-depth interviews, informed the questionnaire design, validity testing, and experimental setup. Furthermore, five technologists, including innovators, robotics developers, and academics, participated in semi-structured interviews to identify key factors influencing user satisfaction.

3.2. Research Instruments

This study employs a range of research instruments to collect, measure, and analyze data on emotional interactions with intelligent home products. Quantitative tools such as questionnaires, interview forms, and observation sheets will be used, along with validated scales commonly applied in empirical research, to assess affective interaction and communication effectiveness.

Lewin's force field analysis method will be a key tool for examining the dynamics among the three core elements of the communication system: user, intelligent product, and environment. Participants will be invited to complete an interactive context analysis diagram before interviews or surveys. This diagram represents the user, product, and environment as three dimensions. Users draw arrows to indicate driving (positive) and restraining (negative) forces, with arrow length reflecting the strength of each factor. This user-generated visual map helps identify key influences and their intensities within a specific interaction context.

3.3. Interviewing Forms and Questionnaires

The study will begin with in-depth, face-to-face interviews with professional users using a structured interview form. These interviews aim to understand intelligent home product development's current state and limitations. Insights from these interviews will refine the initial questionnaire draft, ensuring it is scientifically sound and practical. Additionally, interview findings will inform the design of the validity scale and the implementation of the interaction design experiment.

The finalized questionnaire will be administered to a stratified sample of 400 households in Shanghai, each typically comprising 1–7 members. The data collected will help identify key communication elements involved in user interaction with intelligent home products, ultimately supporting the development of an emotional interaction design model. The questionnaire may be reused in different phases of the research and adjusted as needed to align with evolving research objectives.

3.4. Observation Forms and Validity Scale

This study will also include an emotional interaction test using design sketches to validate the effectiveness of the proposed communication model. Validity scales will be employed to assess complex emotional responses and user experiences. The scale design will draw on established instruments, such as the Interpersonal Communication Satisfaction Inventory [18] which has demonstrated reliability coefficients between 0.72 and 0.93. Modified versions of this scale have also shown strong reliability [19]. The adapted scale will evaluate user interaction experiences and support the study's conclusions.

In addition, observation forms will be used during the sketch-based interaction tests. Without interfering with participants, researchers will observe and record the difficulty and fluency of user operations. These observations will help determine whether the interaction design meets the intended communication and usability goals.

3.5. Research Design

The research design centres on the study's core objective: constructing a *Hybrid Communication Model of Intelligent Home Products* to guide emotional interaction design. It follows a logical sequence from developing the initial conceptual model to data collection, analysis, and empirical validation. The central focus is on data collection, screening, and validation. Data is gathered, analyzed, and synthesized, with iterative validation conducted as needed to ensure reliability. This rigorous process supports the effective development of the communication model.

4. Results and Analysis

4.1. Impact Factor Screening and Organizing the List

The study uses qualitative and quantitative evaluations to analyze interaction design cases and literature to identify key factors influencing human-machine communication in intelligent home products. Factor selection follows four principles: the particularity of home products, considering diverse user backgrounds; typicality, ensuring cross-category relevance while accounting for product-specific features; integrity, covering the full interaction lifecycle and genuine user needs; and a balance of objective and subjective perceptions, combining observable behaviours with internal user experiences [18]. The process involves categorizing macro-level factors based on communication and ergonomics disciplines, extracting detailed factors from literature, and validating findings through case studies and observation to ensure a comprehensive, reliable framework.

4.2. User

User-level factors influencing human-machine communication in Table 1 include four main categories: user cognitive load, interaction skills, interaction expectations and personalization. Cognitive load relates to users' comprehension, memory and perceptive abilities, which affect how easily they understand and operate interface logic. Interaction skills cover visual, voice, haptic, olfactory and taste-based capabilities, along with multilingual proficiency, all of which contribute to the fluency and accuracy of interaction. Expectations vary by task type; users expect higher precision for critical functions (e.g., microwaves) and are more flexible with casual devices (e.g., smart speakers) [19]. Personalization involves age, gender, habits, aesthetic preferences, and cultural background, influencing whether users prefer voice-based, visual or physical interfaces. Collectively, these factors highlight the importance of designing adaptive, intuitive systems that accommodate diverse user abilities, experiences, and preferences.

Table 1.
Classification of user-level factors.

Users			
User Cognitive Load	**User interaction skills**	**User Interaction Expectations**	**User personalization**
comprehension	level of proficiency	Precision Interaction	Area
perceptive and observational ability	Visual interaction skills	Interaction fluency	Age
logical interaction ability	Voice interaction skills	Fuzzy interaction	Gender
ability remember	Olfactory Interaction skills		Habit
	Haptic interaction skills		Esthetics & Preferences
	Taste Interaction Skills		Culture & Background
	Multilingual capability		

4.3. Intelligent Products and Emotional Communication

Factors influencing human-machine communication at the intelligent product level include interface design, interaction naturalness, technology adaptability, and ethical considerations such as data privacy. Effective interface design focusing on visual appeal, usability, and coherence in elements like fonts, colours, graphics, and sound is central to shaping user experience. For instance, Apple's iOS employs minimalist layouts and fluid transitions to enhance clarity and usability. At the same time, China's Quark Browser emphasizes simplicity and speed through streamlined design and voice interaction, reducing cognitive load. In addition to traditional graphical interfaces, emerging interaction modes such as somatosensory, gesture-based, and facial expression interactions are reshaping the user experience. These methods aim to be intuitive, multimodal, and easy to learn, though their success also depends on users' tolerance for minor errors.

A notable example is the *Ambi Night Light*, designed by Stephen Lynn (Figure 4). This product leverages embodied interaction through touch and long-press controls. Its intuitive design supports children's usage by offering a simple, tactile, and emotionally engaging experience, thus reducing learning difficulty and enhancing emotional connection. It exemplifies how intelligent products can create more natural, meaningful interactions that transcend functionality.

As an extension of these interaction strategies, emotional communication shifts the focus from accurate information transmission to generating emotional resonance. While traditional interfaces ensure clarity, more ambiguous yet expressive cues such as gestures, light patterns, tactile responses, and music are increasingly used to convey mood and atmosphere. Intelligent products now integrate adaptive features to personalize emotional responses, enhancing user engagement. However, this advancement also introduces challenges, including system delays, integration issues, and growing privacy concerns. For instance, Apple Smart Home prioritizes user privacy in emotional data handling. However, collecting and using emotional data for targeted advertising or algorithm-driven emotional amplification can lead to "information cocoons," subtly shaping users' behaviours and perceptions. Designers must carefully balance innovation with ethical responsibility and emotional well-being as intelligent products evolve to engage users functionally and emotionally.

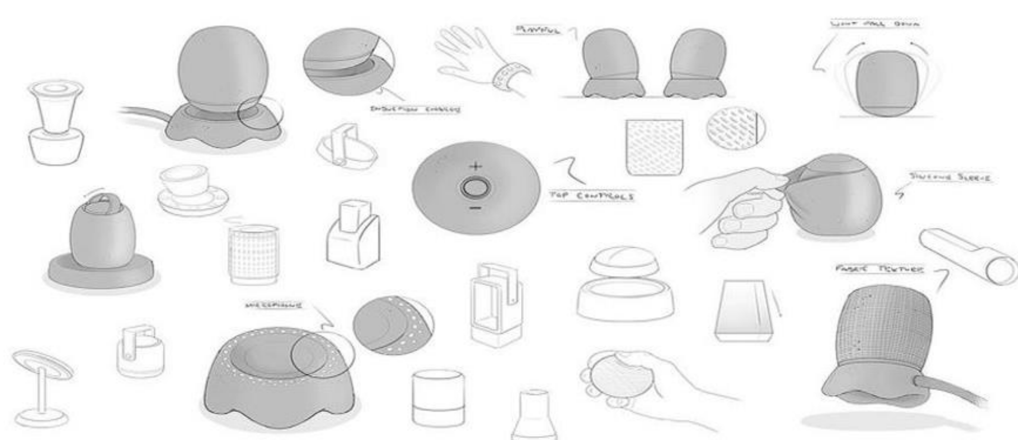

Figure 4.
Ambi night light Interaction Design.

4.4. Design Dimensions Influencing Human-Machine Communication in Intelligent Products

Table 2 outlines six core design dimensions influencing human-machine interaction at the intelligent product level. Product appearance design includes elements like colour, material, and styling, which affect aesthetics and user perception. Other interaction designs, such as soundscapes and tactile feedback, enhance sensory engagement. Interface design focuses on graphics and fonts to support clarity and usability, while interaction design ensures fluency and minimizes learning effort.

The friendly design emphasizes inclusivity through age-friendly, barrier-free, and safe features. Technically sound design ensures compatibility across hardware, software, and environments, supporting reliability and seamless integration. Together, these factors guide the creation of user-centric, accessible, and emotionally responsive intelligent products.

Table 2.
Classification of intelligent product-level factors.

Intelligent product					
Product Appearance Design	**Other Interaction Designs**	**Interface Design**	**Interaction Design**	**Friendly Design**	**Technically Sounds**
Colour	Surface Finishing	Interaction Method Graphics	Font	Age-friendly design	Hardware-software compatibility
Material	Colour	Interaction fluency	Learning Costs	Barrier-free design	Product environment compatibility
	Product Styling			Safety design	
	Soundscape				

4.5. Environmental Influences on Human-Machine Interaction

The environment significantly shapes human-machine interaction across physical, social, technological, economic and psychological dimensions, as shown in Table 3. The physical environment, such as confined or mobile spaces (e.g., cars or bathrooms), demands tailored interaction designs, simplified vehicle interfaces or challenges like Tesla's frozen door handle in cold weather [20]. The social environment, including cultural norms, education, and technological acceptance, influences interface preferences; for instance, touch and voice interfaces are standard in open, tech-savvy societies, while conservative regions lean toward physical controls. Cultural context matters, too. High-context cultures (e.g., China) rely more on implicit communication than low-context cultures (e.g., the U.S.). The technological and economic environments dictate access to and integration of intelligent systems, with wealthier regions advancing more rapidly. However, this creates a risk of technological disparity and digital colonization in underdeveloped areas. The psychological environment, shaped by events like COVID-19, also drives behavioural shifts, accelerating the move toward remote and online interactions [19].

Table 3.
Classification of environments-level factors *influencing human-machine communication.*

Environments	Physical environment
	Social environment
	Technical environment
	Economic environment
	Psychological environment

4.6. Analysis of Respondents' Demographics and Smart Product Usage Trends

Table 4 presents the demographic characteristics and bright product usage patterns of the 400 valid survey respondents. The gender distribution is nearly balanced, with 52.75% female and 47.25% male participants, indicating no gender bias in the sample. Age distribution is concentrated between 18 and 40 years (76.42%), with the largest segment being the 26–30 age group (27.16%), followed by 18–25 (25.47%) and 31–40 (23.79%). These groups represent the digitally active population with high receptiveness to innovative technologies. Respondents under 18 (5.89%) and over 60 (3.16%) were marginal due to limited autonomy and technological adaptability. In terms of family structure, partner households (27.25%), multigenerational families (27.5%), and families with children (26.6%) dominate, reflecting typical urban living arrangements in Shanghai. Non-traditional structures (21.75%), including individuals living alone or with pets, indicate evolving social trends and diverse product needs. Home activities are primarily work- or study-related (83.25%), highlighting how innovative technologies support multifunctional living spaces. Familiarity with smart products is high (80%), though most users (61.25%) are still in a wait-and-see phase, showing cautious engagement. Meanwhile, 37.75% have hands-on experience, suggesting increasing user involvement and market potential for deeper integration of smart home systems.

Table 4.
Demographic Profile and Smart Product Usage of Respondents.

Category	Subcategory	Number (n=400)	Percentage (%)
Gender	Male	189	47.25
	Female	211	52.75
Age Group	Under 18	24	5.89
	18–25	102	25.47
	26–30	109	27.16
	31–40	95	23.79
	Over 60	13	3.16
	Others	57	14.26
Family Structure	Partner household	109	27.25
	Multigenerational family	110	27.50
	Family with children	106	26.60
	Non-traditional (e.g., solo, pets)	87	21.75
Main Home Activity	Work-study	333	83.25
Smart Product Familiarity	Familiar with smart products	320	80.00
Smart Product Usage	Hands-on experience	151	37.75
	Wait-and-see phase	245	61.25

4.7. Reliability and Validity Analysis of the Measurement Scale

Table 5 presents the reliability test results for the 20-item scale to assess users' communication and emotional interaction experiences with smart home products. The Corrected Item-Total Correlation (CITC) values for all items range from 0.452 to 0.654, exceeding the recommended threshold of 0.3, indicating that each item correlates with the overall scale and contributes positively to internal consistency. The Cronbach's Alpha if Item Deleted values for all items remain consistently above 0.9, suggesting that removing any single item would not improve overall reliability, and thus, all items are retained. The scale's overall Cronbach's Alpha is 0.913, reflecting the instrument's excellent internal consistency and reliability. These results confirm that the measurement tool is psychometrically sound for further analysis, such as modelling user behaviour and informing innovative product optimization strategies. The scale's structure is also statistically valid, supported by a high KMO value of 0.952 and a significant Bartlett's Test ($p = 0.000$), indicating sampling adequacy and strong inter-item correlations suitable for factor analysis.

Table 5.
Corrected Item-Total Correlation and Cronbach's Alpha.

	Corrected Item-Total Correlation (CITC)	Cronbach's Alpha
X01	0.528	0.910
X02	0.533	0.910
X03	0.522	0.910
X04	0.504	0.911
X05	0.452	0.912
X06	0.521	0.910
X07	0.489	0.911
X08	0.512	0.910
X09	0.514	0.910
X10	0.461	0.911
X11	0.637	0.907
X12	0.606	0.908
X13	0.627	0.908
X14	0.594	0.909
X15	0.585	0.909
X16	0.654	0.907
X17	0.574	0.909
X18	0.623	0.908
X19	0.608	0.908
X20	0.633	0.907

4.8. Factor Extraction

Table 6 shows the factor variance for each item before and after extraction. The "Original" values are all set at 1.000, while the "After Extraction" values range from 0.520 to 0.659. Most items show a variance between 0.5 and 0.7, indicating strong representation by the extracted factors. The extracted factors explain over 52% of the variance, demonstrating effective factor consolidation and maintaining significant information. These results affirm the reliability and validity of the measurement tool.

Table 6.
Ccommon factor variance.

	Original	after extraction
X01	1.000	0.606
X02	1.000	0.541
X03	1.000	0.563
X04	1.000	0.539
X05	1.000	0.555
X06	1.000	0.520
X07	1.000	0.564
X08	1.000	0.567
X09	1.000	0.550
X10	1.000	0.534
X11	1.000	0.639
X12	1.000	0.573
X13	1.000	0.653
X14	1.000	0.605
X15	1.000	0.644
X16	1.000	0.659
X17	1.000	0.603
X18	1.000	0.627
X19	1.000	0.603
X20	1.000	0.627

4.9. Extraction Method: Principal Component Analysis

The Principal Component Analysis (PCA), shown in Table 7, yielded two extracted factors, with the following variance contributions: the first factor explained 31.106%, and the second factor explained 27.742%, for a cumulative contribution of 58.848%. It means that approximately 59% of the original data's variance was captured by these two factors, which is considered ideal for factor extraction, as suggested by Wu [12]. The total variance from all 20 variables was 100%, with the first two factors explaining a substantial portion, demonstrating effective dimensionality reduction while maintaining a high level of information from the original dataset. Factors 3 to 20 contributed smaller amounts to the total variance, with individual eigenvalues progressively declining. The first two factors were the most significant, suggesting they represent the core dimensions underlying the data, while the remaining factors had diminishing contributions. It supports the appropriateness of the extracted factors in representing the data structure.

Table 7.
Total Variance Explained by Principal Component Analysis.

ingredient	Initial eigenvalue			Extract the sum of the squares of the loads			Rotational load sum of squares		
	total	Variance %	Cumulative %	total	Variance %	Cumulative %	total	Variance %	Cumulative %
1	7.579	37.893	37.893	7.579	37.893	37.893	6.221	31.106	31.106
2	4.191	20.955	58.848	4.191	20.955	58.848	5.548	27.742	58.848
3	0.700	3.499	62.347						
4	0.653	3.267	65.614						
5	0.605	3.023	68.637						
6	0.564	2.820	71.457						
7	0.530	2.651	74.108						
8	0.509	2.544	76.652						
9	0.489	2.447	79.099						
10	0.479	2.397	81.496						
11	0.458	2.292	83.788						
12	0.446	2.231	86.019						
13	0.419	2.094	88.113						
14	0.402	2.009	90.122						
15	0.378	1.890	92.012						
16	0.345	1.727	93.739						
17	0.334	1.672	95.411						
18	0.313	1.567	96.977						
19	0.309	1.544	98.521						
20	0.296	1.479	100.000						

4.10. Extraction Method: Principal Component Analysis

After factors were extracted, Kaiser normalization with Varimax rotation was employed to enhance interpretability. The resulting rotated factor loading matrix, presented in Table 9, reveals the underlying structure by redistributing variance more clearly across two extracted components (factors). This transformation enables better identification of variable-group associations. The factor score coefficient matrix was used to build factor score equations for the two components, which are defined as follows:

Factor 1 (F1): $F1 = (0.574)X1 + (0.577)X2 + \ldots + (0.693)X20$

Factor 2 (F2): $F2 = (0.526)X1 + (0.455)X2 + \ldots + (-0.394)X20$

Considering their variance contribution rates, 31.106% for F1 and 27.742% for F2—a composite factor score (F) is calculated to represent an overall evaluation metric:

$F = 0.31106 \times F1 + 0.2774 \times F2$

This weighting reflects the relative importance of each factor based on the proportion of explained variance. The rotated factor matrix shown in Table 9 illustrates the variable loadings on each factor after rotation. This step significantly improves factor clarity. For instance, variable X1 initially loaded 0.574 on F1 and 0.526 on F2, indicating a dual association. After rotation, its loading on F1 dropped to 0.111, while its loading on F2 increased to 0.770, clearly reassigning it to Factor 2. Similar reassignments are observed across variables, leading to more distinct factor groupings.

Table 9.
Factor Matrix[a].

	1	**2**
X16	0.713	-0.388
X11	0.697	-0.392
X20	0.693	-0.383
X13	0.689	-0.423
X18	0.684	-0.4
X19	0.669	-0.394
X12	0.667	-0.357
X14	0.656	-0.418
X15	0.65	-0.471
X17	0.638	-0.443
X02	0.577	0.455
X01	0.574	0.526
X03	0.567	0.492
X06	0.566	0.447
X09	0.559	0.487
X08	0.557	0.507
X04	0.548	0.489
X07	0.533	0.529
X05	0.496	0.556
X10	0.504	0.529

4.11. Rotation Method: Kaiser Normalised Maximum Variance Method

Table 10 presents the rotated component matrix using the Kaiser Normalised Varimax method, which clarifies the factor structure by maximizing the variance of loadings across components. Factor 1 is defined by variables X11 to X20, all showing strong loadings between 0.743 and 0.801, indicating a coherent underlying construct with minimal cross-loadings. Factor 2 comprises variables X01 to X10, each loading highly between 0.704 and 0.770, with weak associations to Factor 1.

Table 10.
Rotated Component Matrix.

	Factors	
	1	**2**
X15	0.801	0.047
X13	0.801	0.109
X16	0.797	0.151
X11	0.787	0.138
X18	0.782	0.123
X20	0.779	0.143
X17	0.774	0.061
X14	0.772	0.091
X19	0.767	0.119
X12	0.743	0.146
X01	0.111	0.77
X07	0.077	0.747
X08	0.11	0.745
X05	0.033	0.744
X03	0.127	0.74
X09	0.124	0.731
X10	0.056	0.728
X04	0.115	0.725
X02	0.159	0.718
X06	0.156	0.704

4.12. Influencing Factors and User Preferences in Smart Home Design

As shown in Table 11, two main components were identified. Factor 1 (31.106%) reflects emotion and feeling-oriented aspects, including surprise, fun, security, trust and user familiarity. Factor 2 (27.742%) represents efficiency and result-oriented aspects, such as information accuracy, adaptability, and systematization. Emotional factors slightly outweigh rational ones influencing user interaction with smart home systems. Survey results show that 72.5% of users favoured personalized scenarios, and over 70% supported blending real, virtual, and hybrid spaces. Real environments were rated the highest. The study suggests a design approach of entity-based, hybrid-led, virtual supplement supported by AR and environmental sensing technologies.

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Table 11.
Main influencing factors and percentage ranking.

factor1: (31.106%)	X15	Surprise Design	"Emotion and Feeling"-oriented factors
	X13	Fun Design	
	X16	sense of security	
	X11	User Inclusiveness	
	X18	user confidence	
	X20	user familiarity	
	X17	User trust	
	X14	Embodied Design	
	X19	user expectations	
	X12	User Learning Costs	
factor2: Rational factor (27.742%)	X01	Efficiency of information output	"Efficiency and Results"-oriented factors
	X07	configurable	
	X08	Accuracy of information	
	X05	proactive design	
	X03	adaptive	
	X09	adaptive	
	X10	naturalness	
	X04	user expectations	
	X02	Efficiency of information reception	
	X06	systematization	

4.13. participants

Five professional users of intelligent home appliances were interviewed, according to Table 12, including product designers and senior researchers in intelligent interaction. Screening criteria were as follows:

1. At least 3 years of experience in intelligent product design, management, or research.
2. A relevant degree in a related field.
3. Age between 25 and 55 years.

Asterisks denote interviewees particularly interested in the metaverse, whose responses are the focus of this paper. Before the in-depth interviews, participants were asked to draw an interactive scene analysis diagram depicting the factors influencing human-machine interactions in a metaverse context. This diagram comprised three dimensions: user, intelligent product, and environment. Arrows in the diagram represented driving forces (positive) and restraining forces (negative), with their length indicating the strength of each factor. This user-led graphic helped identify specific factors impacting user experience across these dimensions. The semi-structured interviews [4] lasted between 45 and 90 minutes. They included initial questions, allowing flexibility to explore topics in depth. The interview protocol guided the discussion, but the flow remained open-ended and adaptable.

Table 12.
Interviewee List.

#	**Position**	**Field of Work**
1	Senior academic and industry	Product design
2	Senior academic and industry ★	Product design
3	Senior industry	Robot design
4	Senior academic and industry ★	Intelligent interaction
5	Senior industry ★	Online game

4.14. Data Analysis Approach

The interview analysis used Grounded Theory, a positivist qualitative methodology, to develop theory from data by identifying key concepts [21]. First, interviews were transcribed into electronic documents and printed for easy coding. Initial codes were assigned to significant data segments, accompanied by memos to document insights and guide refinement. A constant comparative method was employed to identify similarities and differences across data segments, leading to the adjustment of codes. Finally, categories and patterns were integrated into a coherent theoretical model.

4.14.1. Key Influencing Factors: Insights from Factor Analysis and Expert Interviews

15 key factors influencing user interaction were identified through factor analysis and expert interviews. These factors were categorized into two groups: Design-Optimizable Factors , comprising nine elements directly tied to the interaction scene, such as interface design, emotional engagement, adaptability and usability, which can be enhanced through short-term design interventions; and User-Centric Factors consisting of 6 elements related to personal attributes like personality traits, behavioural habits, and societal regulations, which are less easily influenced but crucial for long-term interaction outcomes. Expert insights underscored the pivotal role of social dynamics in emotional engagement, highlighting aspects such as interaction atmosphere, peer influence, and cultural trends as significant user experience drivers. One expert noted, "Children are more inclined to favour products endorsed by peers," emphasizing the emotional weight of social recognition in shaping user preferences.

As illustrated in Figure 5, children in a warm and joyful social setting were more receptive to engaging with an unfamiliar mechanical dog. It suggests that positive social contexts enhance emotional acceptance and interaction, even with unfamiliar or artificial agents.

Figure 5.
Children interacting with a mechanical dog in a natural state.

4.14.2. The Role of Social Context in Emotional Interaction

Interviewees emphasized the benefit of embedding surprise elements such as playful quirks or intentional, non-critical design "errors" to make intelligent products feel human-like. These elements enhance emotional engagement, especially in leisure-oriented interactions.

However, concerns emerged regarding data privacy in metaverse-integrated smart homes. Many interviewees expressed discomfort with the continuous collection and uploading of personal data, citing potential user autonomy and privacy violations. One participant stated, “Control over intelligent home scenarios should be returned to the user, both in real and virtual settings.” Offering users flexible control over system intelligence and data collection can improve perceived security and autonomy, improving satisfaction and emotional comfort.

4.15. Discussion

This study investigates future directions of human-machine communication in intelligent home systems through the lens of the metaverse, using both questionnaire surveys and expert interviews. It identifies 15 factors that positively influence communication between users and intelligent products, with six indirectly improving user satisfaction by enhancing communication quality. Beyond improving usability and perception through design, the study highlights the importance of the content conveyed by intelligent products.

It emphasizes key technological trends shaping future interactions, such as multimodal input/output (e.g., gesture, voice, touch), advanced natural language processing (NLP) for recognizing tone, emotion, and context, and the integration of physical and virtual spaces via AR/VR. In such hybrid environments, intelligent products will respond to user commands and act as proactive agents, analyzing mood, behaviour, and environmental data to enhance user comfort and engagement. The research also raises concerns about trust and authenticity in the metaverse. While intelligent agents may act autonomously, users remain wary of misinformation. Experts suggest that oversight from trusted institutions such as Government bodies or industry leaders may be needed to ensure content credibility, especially as traditional media are still seen as more reliable than intelligent agents.

Furthermore, the study links the evolution of intelligent products to broader AI theory by defining them as "intelligent agents" entities capable of autonomous decision-making and communication. It introduces ethical concerns around data privacy, informed consent, and emotional manipulation. For instance, there is a risk that artificial simulations may substitute fundamental human interactions, weakening genuine social bonds. Further, it called for deeper interdisciplinary collaboration across communication, psychology, computer science, and ergonomics to understand human-machine communication fully. It also notes that current findings, primarily based on home contexts, may not generalize across cultures or settings and encourages future studies to consider personality traits and cultural diversity. Finally, the study refers to China's MIIT 2024 guidelines, which aim to establish over 50 national and industry standards for intelligent homes by 2030. These standards will span safety, interoperability, personalization, and emotional interaction, positioning China as a global leader in smart home innovation. The field is expected to evolve in three phases: basic functional coverage, customized services, and emotionally intelligent interaction.

5. Conclusion and Recommendation

Based on Lewin's field theory, this study investigates human-machine communication in intelligent home systems across three key dimensions: user, intelligent product, and environment. In the user dimension, four main factors: cognitive load, interaction skills, psychological expectations, and personalization are identified, comprising 19 sub-factors such as comprehension, observation, learning, and memorization. Some are innate (e.g., perception), while others (e.g., aesthetics, proficiency) can be improved through design. The intelligent product dimension includes appearance, interaction design, technology compatibility, and user-friendliness, broken down into 21 design-optimizable sub-factors like colour, sound, and graphics. Environmental factors are classified into physical, social, technological, economic, and psychological aspects, emphasizing the need for a stable yet adaptable interaction setting. Key user experience indicators were refined using principal component analysis (PCA) via SPSS, which was informed by prior studies and survey data. A questionnaire explored user perceptions of hybrid communication in future homes, showing a current focus on real-world interaction but highlighting the potential for mixed and virtual reality contexts. Additionally, expert interviews, guided by field and ergonomics theory, explored the prospects and challenges of human-machine interaction within the metaverse.

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The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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