

THE ACCEPTANCE OF HUMANOID ROBOTS: EVIDENCE FROM ROMANIA

**Radu Lucian Blaga^{1*}, Silviu Gabriel Szentesi², Florentina Simona Barbu³,
Maria Sinaci⁴, Luminița Bozdog⁵**

¹⁾²⁾³⁾⁴⁾ "Aurel Vlaicu" University of Arad, Arad, Romania

⁵⁾West University, Timișoara, Romania

Abstract

The diffusion of humanoid robots into domestic environments is an emerging phenomenon that raises new questions about consumer acceptance. Unlike conventional technologies, humanoid robots combine utilitarian functions with social presence, requiring models of adoption. This study examines the role of demographic characteristics - gender, age, income, marital status, and occupational field - in shaping people's acceptance of humanoid robots, still relatively understudied in Romania. Data were collected through a structured questionnaire. Measurement items were adapted from validated scales in prior literature, and the data were analyzed using statistical tests. The findings demonstrate a statistically significant association between demographic variables and consumers' familiarity, comfort, and acceptance of humanoid robots.

The study makes a valuable contribution to the literature, especially through empirical data from the Romanian context, presenting implications for the design and marketing of humanoid robots, offering lessons for demographic segmentation, segmented communication strategies, and phased pricing models.

Keywords

humanoid robots; social acceptance; anthropomorphism; Unified Theory of Acceptance and Use of Technology; adoption barriers; demographics; consumer behaviour.

JEL Classification

O330, M310, M390

Introduction

The rapid advancement of robotics and artificial intelligence (AI) is transforming the way consumers interact with technology in both professional and domestic settings. Among these innovations, humanoid robots represent a particularly intriguing category because they combine utilitarian functions with social and emotional dimensions.

* Corresponding author, **Radu Lucian Blaga** – radu.blaga@uav.ro

Unlike traditional household appliances, humanoid robots are designed to resemble humans in appearance or behaviour, thereby introducing new opportunities for companionship, social presence, and interactive assistance (Mahdi et.al., 2022). Their adoption, however, depends not only on technical capabilities but also on how consumers perceive, evaluate, and integrate them into their daily lives (Kim, 2025). In the context of humanoid robots, perceived utility remains a central determinant, capturing the practical benefits such as cleaning, home assistance, and security (Chen et al., 2025). Understanding the drivers and barriers to humanoid robot acceptance has thus become an important question for both researchers and practitioners seeking to anticipate the diffusion of this technology in the Romanian context.

The global robotics market has grown substantially over the past decade, with service robots moving beyond industrial automation into healthcare, education, and domestic applications. Forecasts suggest that humanoid robots will increasingly enter households as assistants, caregivers, tutors, or companions, supporting activities that range from cleaning and cooking to social interaction and elder care. These developments reflect broader societal trends such as ageing populations, demand for personalized services, and interest in smart-home ecosystems.

Another underexplored dimension is the role of demographics. The Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) identifies gender, age, and experience as moderators, but empirical evidence suggests that demographic variables do more than merely condition existing relationships. Gender differences have been shown to affect emphasis on usefulness versus ease of use (Gefen & Straub, 1997). Age influences sensitivity to usability and risk (Czaja et al., 2006), with younger individuals more receptive to hedonic value and older individuals more focused on effort reduction. Income shapes perceptions of affordability and the willingness to purchase (Venkatesh et al., 2012). Beyond these, variables such as marital status, occupational status, and field of activity may influence comfort and familiarity with humanoid robots, yet remain less studied. Recognizing the centrality of demographics enables segmentation of early adopters, providing valuable insights into which groups are most likely to drive diffusion.

Against this backdrop, the present study investigates consumer acceptance of humanoid robots in Romanian domestic contexts by integrating constructs from technology adoption literature with insights from human–robot interaction (HRI) research.

The contributions of this research are threefold. First, it extends the UTAUT/UTAUT2 framework by incorporating constructs particularly relevant to humanoid robots, such as anthropomorphic features and adoption barriers, thereby addressing the dual utilitarian and social nature of these technologies. Second, it positions demographics not merely as moderators but as central segmentation variables, highlighting their role in shaping early adoption patterns. Third, it provides empirical evidence based on a diverse consumer sample, enabling the identification of both drivers and inhibitors of acceptance across Romanian demographic groups. Together, these contributions enrich theoretical understanding while offering practical perspectives for companies seeking to design, market, and deploy humanoid robots in Romanian household contexts.

In sum, humanoid robots present a frontier of consumer technology that raises novel questions about how people evaluate and accept social machines in everyday life. The

present work serves theoretical and practical ends. Theoretically, it extends the UTAUT/UTAUT2 framework by adding humanoid-robot specific constructs and by recentering demographic factors as the core segmentation categories. At a practical level, the results help raising awareness among robot designers, marketers, and policymakers on the importance of demographic-specific design, communication, and pricing strategies.

1. Review of the scientific literature

Research on technology adoption has long emphasized the role of individual beliefs in shaping behavioral intentions. The Technology Acceptance Model (TAM) proposed by Davis (1989) introduced two key constructs: perceived usefulness (the belief that a technology improves task performance) and perceived ease of use (the belief that a technology is free of effort). Numerous studies have demonstrated the robustness of these constructs across domains, showing that perceived usefulness is typically the strongest predictor of adoption intentions (Davis, 1989; King & He, 2006; Xiao & Goulias, 2022).

Building on TAM, the UTAUT synthesized eight prior models and identified four determinants of intention and use: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). The model also introduced moderators (gender, age, experience, voluntariness), underscoring that demographic characteristics shape the strength of these relationships. Later, UTAUT2 extended the model for consumer contexts by adding hedonic motivation, price value, and habit. This extension demonstrated that consumer adoption is influenced not only by utility but also by enjoyment, cost–benefit evaluations, and behavioral routines.

The UTAUT framework remains one of the most influential in explaining the adoption of frontier technologies, including artificial intelligence (AI), Internet of Things (IoT), and service robots. Momani (2020) emphasizes that UTAUT has been extensively adapted to emerging technology domains, including robotics, and continues to provide predictive power in voluntary-use contexts. Marikyan and Papagiannidis (2025) further argue that UTAUT/UTAUT2 offers a strong foundation for theorizing acceptance but requires contextual enrichment to address innovations characterized by social presence and anthropomorphism, which are highly relevant for humanoid robots.

In this study, perceived utility, adoption barriers, technological experience, and intention to use directly map onto UTAUT/UTAUT2 constructs, while income relates to the price value dimension, and demographics serve as moderators. This theoretical grounding ensures alignment with established technology adoption literature.

While TAM and UTAUT emphasize utilitarian and normative drivers, the HRI literature highlights the importance of anthropomorphism and social presence. Humanoid robots differ from other technologies because their design evokes social cues, such as human-like appearance, voice, or emotional expression. Kiesler et al. (2008) showed that anthropomorphic design increases perceptions of likability, trust, and relational closeness. Similarly, Song and Kim (2022) found that anthropomorphism enhances social presence, fostering trust and thereby strengthening adoption intentions.

The distinctive challenge of humanoid robots lies in their dual nature: they are both tools and social actors. On one hand, consumers evaluate them in terms of perceived

utility, focusing on the ability to perform household tasks efficiently (Schneiders et al., 2023). On the other hand, their acceptance depends on relational cues, such as empathy, likability, or trustworthiness, which reflect their anthropomorphic features (Park & Whang, 2022; van Pinxteren et al., 2019; Spaccatini et al., 2023). Anthropomorphic features include attributes such as empathy, likability, trustworthiness, and pleasantness, which directly shape user comfort and acceptance (Fink, 2012). In the domestic context, anthropomorphism is particularly salient because robots are expected to integrate into intimate environments such as kitchens, bedrooms, or living rooms. Broadbent et al. (2009) demonstrated that acceptance of healthcare robots depended strongly on perceived social presence and relational fit. Thus, in addition to perceived utility, anthropomorphic design provides a pathway for robots to gain social acceptance as companions or assistants.

Despite growing enthusiasm for robotics, consumer adoption is often hindered by perceived barriers. Parasuraman and Colby (2015) highlight cost, complexity, privacy, and security concerns as recurring inhibitors of technology adoption. In the case of humanoid robots, adoption barriers include worries about high purchase costs, technical failures, and integration difficulties in the home (De Graaf et al. 2017; Papadopoulos et al., 2020).

Beyond utility, perceived benefits such as entertainment, companionship, and enjoyment also play a role in acceptance. UTAUT2's construct of hedonic motivation captures this dimension, emphasizing that consumers adopt technologies not only for productivity but also for enjoyment and symbolic value. Marikyan and Papagiannidis (2025) extend this perspective by noting that humanoid robots blur the boundaries between tools and social actors, thereby offering both functional and experiential value. Song and Kim (2022) found that robots perceived as fun or engaging were more readily accepted, even when their functional utility was modest. Thus, in this study, perceived benefits are conceptualized as moderators that can strengthen the link between anthropomorphic features and intention to use.

Demographics play a parallel and often decisive role in shaping the pathways through which technology beliefs influence adoption.

Age has repeatedly been shown to condition how individuals evaluate technologies. Younger consumers are typically more motivated by hedonic value and novelty, which makes them more open to adopting emerging technologies such as humanoid robots for entertainment or companionship purposes (De Jong et al. 2024). In contrast, older consumers are more cautious, placing greater emphasis on effort expectancy, ease of use, and perceived risks (Czaja et al., 2006). This reflects broader life-course differences: while younger individuals may see technology as a natural extension of daily life, older individuals often evaluate adoption through the lens of usability, familiarity, and risk minimisation. Consequently, the same anthropomorphic features that appeal to younger users for social presence may trigger hesitation among older users if they are perceived as complex or intrusive.

Gender differences have also been documented extensively. Gefen and Straub (1997) found that men are more likely to focus on perceived usefulness, evaluating whether a system improves task performance, whereas women tend to emphasize ease of use and social influence. Nomura et al. (2008) found, in an experiment on interactions between a

mechanical humanoid robot and humans, that females had more negative attitudes toward the social impact of robots. These gendered orientations suggest that communication strategies should be tailored differently: functional utility emphasized for male audiences and relational or ease-of-use benefits emphasized for female audiences.

Income, as captured in the price-value construct of UTAUT2, exerts influence through perceptions of affordability. Higher-income consumers are more likely to perceive robots as attainable and worthwhile investments, which increases their purchase intention. Conversely, lower-income consumers may recognize the potential utility of humanoid robots but remain constrained by cost concerns, leading to hesitancy to adopt. This pattern aligns with Parasuraman and Colby's (2015) observation that financial barriers are among the most persistent inhibitors of consumer adoption. Income thus functions not only as an economic resource but also as a psychological filter through which consumers assess whether the perceived benefits of robots justify their cost.

In the context of robotics, the image is defined as the user's belief that using a robot enhances one's image or status in one's social system (Venkatesh & Davis, 2000).

Together, these demographic moderators illustrate that acceptance of humanoid robots is not uniform across society. In our dataset, demographic variables such as age, gender, and social status (marital status, occupational status, and field of activity) were associated with familiarity, comfort, and purchase intention. These associations reflect the UTAUT moderator logic, in which demographic segments alter the pathways to adoption.

The above literature review suggests that the adoption of humanoid robots depends on a combination of utilitarian, social, and demographic factors. TAM and UTAUT/UTAUT2 explain intention through utility, effort, social influence, hedonic motivation, and price value. HRI literature highlights anthropomorphic features and social presence as unique drivers. Demographics further moderate these relationships, influencing familiarity, comfort, and willingness to purchase.

By addressing the identified gaps, the present study makes several contributions to the existing body of literature on technology acceptance and human–robot interaction. First, it extends the UTAUT/UTAUT2 framework. While UTAUT2 highlights performance expectancy, social influence, hedonic motivation, and price value, it does not explicitly capture the role of anthropomorphic features or the comfort of interacting with human-like agents. By integrating constructs such as empathy, likability, and trustworthiness, this study accounts for the fact that humanoid robots are not merely functional tools but also social actors that evoke relational responses. Finally, the construct of perceived benefits extends the traditional utilitarian and hedonic dimensions by incorporating expectations of companionship, entertainment, and household assistance, thus reflecting the multidimensional value proposition of humanoid robots.

Second, this study positions demographic factors as more than simple moderators. Prior applications of UTAUT often treated demographics such as age, gender, or experience as variables that only condition the strength of relationships among constructs. However, mounting empirical evidence suggests that sociodemographic attributes actively shape familiarity, comfort, and intention, making them central for understanding early adoption. By foregrounding variables such as age, gender, income,

marital status, and occupational field, this study demonstrates that the acceptance of humanoid robots cannot be fully explained without considering demographic segmentation. This approach resonates with the logic of consumer behavior research, where market segments are defined not only by psychological drivers but also by socio-economic and lifestyle characteristics.

Third, the study makes an empirical contribution by testing associations between demographic variables and acceptance outcomes in a diverse consumer sample. Much of the prior literature has focused either on narrow populations (such as students or professionals) or on theoretical modelling without sufficient demographic heterogeneity. By analyzing responses from a broad and varied sample, the present research can uncover patterns that are both statistically significant and substantively meaningful, even when effect sizes are modest. In doing so, the study provides insights into which consumer groups are more familiar with, comfortable around, and willing to adopt humanoid robots, offering practical guidance for both researchers and industry stakeholders.

Together, these contributions enrich the theoretical landscape by demonstrating that models of technology acceptance must evolve to capture the social, experiential, and demographic dimensions that characterize consumer encounters with humanoid robots. The study thus bridges the gap between traditional acceptance frameworks and the unique challenges posed by emerging technologies that combine utilitarian functions with human-like features.

2. Research methodology

2.1 Research design

This study employed a quantitative, survey-based design to explore relationships between demographic variables and consumer perceptions of humanoid robots. Rather than testing a formal structural model, the analysis was guided by a set of research questions, each formulated to examine whether sociodemographic factors such as gender, age, income, education, occupation, or field of work are significantly associated with respondents' familiarity, comfort, acceptance, and purchase intentions regarding humanoid robots. In Romania, research on this topic remains limited. Such an approach is consistent with exploratory consumer research where the primary objective is to capture associations rather than to establish causality (Conner et al., 2017; Pace, 2021). Bivariate chi-square tests were considered suitable for the exploratory purpose of identifying demographic segmentation patterns, as the variables are categorical. Multivariate methods might provide further insight, but they are not covered in the current exploratory study and are proposed for future work. Chi-square analysis does not capture interaction effects or causal relationships and may yield small effect sizes in heterogeneous samples. These limitations are recognised and serve to motivate future multivariable extensions.

2.2 Research questions

Prior studies on technology adoption highlight that demographic factors significantly shape familiarity with emerging technologies (Venkatesh and Morris, 2000; Cooper, 2006). Occupational status and field of work are also linked to exposure: individuals

working in technology-intensive domains demonstrate greater awareness and familiarity with robots than those in traditional sectors (Pelau et al., 2021). Accordingly, the study examines whether **gender**, **occupational status**, and **field of activity** are associated with **familiarity with humanoid robots**.

RQ1. Is gender associated with familiarity with humanoid robots?

RQ2. Is occupational status associated with familiarity with humanoid robots?

RQ3. Is the field of work associated with familiarity with humanoid robots?

Comfort in interacting with robots has also been shown to depend on social and contextual factors. Research suggests that workplace environment, cultural attitudes, and personal background contribute to whether individuals feel at ease engaging with robotic systems (Law et al., 2021). Marital status may further influence perceptions of domestic technologies, as household structures shape expectations and comfort levels with automation in daily life (Broadbent et al., 2009). Therefore, we investigate whether the **field of work** and **marital status** are associated with **comfort level when interacting with humanoid robots**.

RQ4. Is the field of work associated with comfort in interacting with humanoid robots?

RQ5. Is marital status associated with comfort in interacting with humanoid robots?

Acceptance and purchase intentions are traditionally driven by age and income, two variables consistently found to influence consumer adoption of new technologies. Younger cohorts tend to be more open to technological innovations, while older individuals are often more hesitant (Wu et al., 2014; Baisch et al., 2017). Similarly, higher-income groups demonstrate stronger purchase intentions, reflecting affordability and willingness to invest in advanced products (Venkatesh et al., 2012). Gender has also been shown to influence acceptance, as men are more likely to express enthusiasm for robotics and automation (Nomura et al., 2006). In this context, the study addresses whether **gender**, **age**, and **income** are associated with **acceptance and purchase intentions for humanoid robots**.

RQ6. Is gender associated with the acceptance of humanoid robots?

RQ7. Is age associated with the intention to purchase humanoid robots?

RQ8. Is income associated with the intention to purchase humanoid robots?

By posing the analysis as research questions, the study adopts a more exploratory stance while still relying on hypothesis-testing statistical procedures, such as chi-square tests of independence.

2.3 Sampling and data collection

Data were collected using a structured questionnaire administered online. The survey targeted a broad population of adult respondents in Romania, with no restrictions on profession or background, to capture heterogeneous views on humanoid robots. A total of 503 valid responses were included in the final dataset.

The sampling procedure was non-probabilistic, relying on voluntary participation through online distribution channels. While this approach does not allow for claims of full representativeness, it aligns with similar studies in consumer and technology acceptance research where access to random sampling is limited (Baker et al., 2013; Makwana et al., 2023). The rationale was to ensure sufficient demographic variation

across age, gender, education, income, and occupational sectors to examine meaningful associations.

2.4 Measures

The questionnaire included both demographic variables and perception-related items. For demographic variables, respondents reported their gender, age, education level, income category, marital status, occupation, and field of work. These served as independent grouping variables for the statistical tests.

Perception items gather information on familiarity with robots, comfort in interacting with humanoid robots, general acceptance, and intention to purchase such robots for domestic use. All items were measured using categorical or ordinal scales, enabling cross-tabulation with sociodemographic variables.

The items were adapted from previous studies in human–robot interaction and consumer technology research (Premathilake & Li, 2024), but simplified to suit the exploratory design of this study.

2.5 Data analysis procedure

The analysis was conducted using SPSS 26 (IBM), with a focus on non-parametric statistical techniques appropriate for categorical data. The main procedure applied was the chi-square test of independence, which evaluates whether two categorical variables are statistically associated. For each test, the following indicators were reported: Chi-square statistic (χ^2) and its p-value to assess statistical significance. Cramer's V or Phi coefficient (depending on variable size) to measure the strength of the association.

This approach allows us to determine not only whether relationships exist but also whether they are weak, moderate, or strong. According to conventional benchmarks (Cohen, 1988), Cramer's V values of 0.10, 0.30, and 0.50 correspond to small, medium, and large effects, respectively.

Chi-square analysis was selected because it is a robust method for categorical data and is widely used in exploratory consumer research (Pace, 2021). Unlike regression or structural equation modelling, chi-square does not assume interval-level measurement or normal distribution, making it suitable for the current dataset.

2.6 Validity and reliability considerations

Although chi-square tests provide useful descriptive insights, they do not establish causality. To address this limitation, the study emphasizes the exploratory nature of the research questions. The non-probabilistic sampling method introduces potential biases in representativeness, which should be considered when interpreting the results. However, the heterogeneity of the sample ensures a broad range of demographic perspectives is captured, thereby enhancing the practical relevance of the findings.

Moreover, reporting both significance (p-values) and effect sizes (Cramer's V, Phi) ensures transparency and allows readers to evaluate not only whether associations exist, but also their practical magnitude.

In summary, the methodology employs an exploratory, association-based approach, utilising chi-square tests to investigate how demographic characteristics influence perceptions of humanoid robots. By framing the investigation as a series of research

questions rather than strict hypotheses, the study acknowledges its exploratory character while still providing quantifiable evidence of relationships between variables. This approach is consistent with applied consumer research published in journals with a practical focus, where the objective is to highlight actionable insights rather than to build complex theoretical models.

3. Results and discussion

The survey sample consisted of 503 valid Romanian respondents. In terms of gender, women were slightly overrepresented (59.7%) compared to men (39.6%), while only 0.8% identified as other.

Regarding age, the majority of participants were young adults: 45.8% were aged 18–24, followed by 14.7% aged 25–34 and 13.7% aged 35–44. Another 13.7% fell into the 45–54 category, while 7.2% were between 55–64, and 3.6% were 65 or older. Very few respondents (0.4%) were younger than 18. This distribution indicates that the dataset is heavily oriented toward younger cohorts.

Regarding education, most respondents had attained higher education: 45.9% held a bachelor's degree, 19.0% a master's, and 9.4% a doctorate. About a quarter (25.0%) had completed high school, while only 1.0% reported primary or secondary education.

In terms of monthly income, the largest group earned under 3,000 RON (30.2%). The next categories were 3,000–4,500 RON (20.5%) and 4,501–6,000 RON (19.9%). Higher-income groups were less represented: 11.7% earned between 6,001–7,500 RON, 6.4% between 7,501–9,000 RON, 4.8% between 9,001–10,500 RON, and only 6.6% over 10,500 RON.

As for marital status, nearly half were married (48.1%), 34.0% single, 11.9% divorced, 5.0% widowed, and 1.0% other.

Looking at occupational status, most respondents were employed (53.5%) or students (34.8%). A small share were retired (3.2%), unemployed (1.8%), or reported another status (2.8%). Finally, the fields of work showed broad heterogeneity. The largest single category was “other” (29.4%), followed by education (16.5%), finance and banking (12.3%), commerce (10.1%), and technology/IT (10.7%). Smaller groups were found in healthcare (4.4%), industry/production (5.6%), public administration (6.0%), tourism (2.0%), agriculture/forestry (1.4%), culture (1.0%), and law (0.6%).

The distribution shows that the sample includes both younger and older respondents, with a relatively balanced gender composition. Educational levels are predominantly higher (Bachelor's and Master's), reflecting the profile of online survey participants. Income distribution was skewed toward lower income brackets, but all income brackets were represented, allowing exploration of differences across socioeconomic groups.

To further explore the associations between demographic variables and respondents' attitudes toward humanoid robots, chi-square tests of independence were conducted. The results present the strength of the associations using Cramér's V coefficients (Figure no.1), and the darkly coloured bars denote statistically significant relationships ($p < 0.05$).

The analysis revealed that occupational status and field of activity were significantly associated with familiarity with robots, suggesting that individuals employed in certain domains—particularly those with higher exposure to technology—tend to report greater

familiarity. Additionally, the living environment (urban vs. rural) displayed a weaker, non-significant association, indicating that geographic context may play a less decisive role.

When considering comfort in interacting with robots, significant associations emerged with field of activity, marital status, and income levels. Respondents from technical or service-oriented sectors, as well as married participants, reported higher comfort levels. Interestingly, education showed only a weak, non-significant association with comfort, despite its association with familiarity.

Overall, the results suggest that familiarity is primarily shaped by professional and occupational exposure, while comfort is more strongly tied to personal context and lifestyle variables. These findings align with prior research highlighting that acceptance of humanoid robots is not determined solely by technological literacy, but also by broader socio-demographic and experiential factors.

The research questions were tested using chi-square tests of independence and are presented in the form of a summary of the results (table no. 1).

Effect sizes (Cramer's V) range between 0.11 and 0.19, indicating small to moderate associations (table no. 1). This suggests that demographic factors do not fully determine perceptions but provide relevant segmentation patterns.

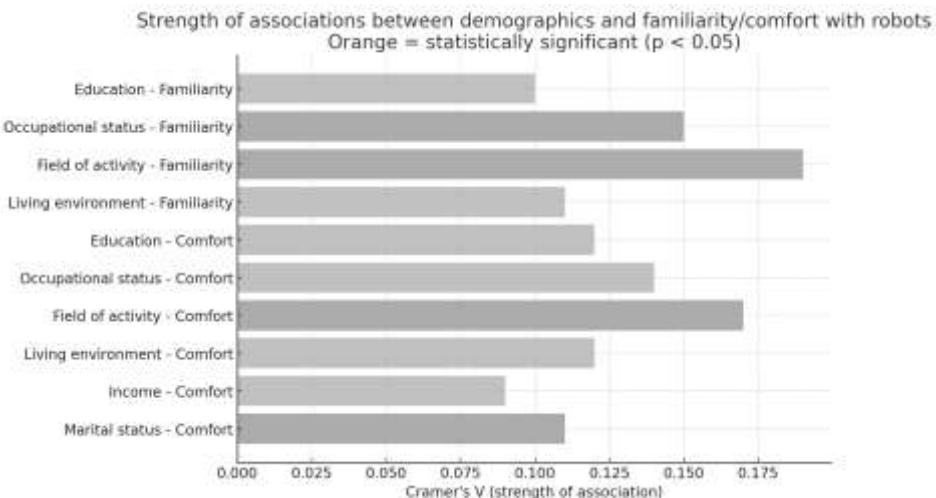


Figure no. 1: Strength of associations between demographics and familiarity/comfort with robots (Cramer's V)

Source: author's contribution

Table no. 1. Results of chi-square tests of independence

Research question (association tested)	χ^2	p-value	Cramer's V	Significance
RQ1: Gender \times Familiarity with robots	17.713	0.023	0.133	Supported
RQ2: Occupational status \times Familiarity	48.450	0.002	0.155	Supported
RQ3: Field of work \times Familiarity	74.910	0.003	0.193	Supported
RQ4: Field of work \times Comfort with robots	63.855	0.027	0.178	Supported
RQ5: Marital status \times Comfort with robots	27.590	0.035	0.117	Supported
RQ6: Gender \times Acceptance of robots	21.988	0.005	0.148	Supported
RQ7: Age \times Intention to purchase robots	43.625	0.030	0.147	Supported
RQ8: Income \times Intention to purchase robots	37.057	0.043	0.136	Supported

Source: author's contribution

- **RQ1–RQ3: Familiarity with humanoid robots**

The results show that gender, occupational status, and field of work are significantly associated with respondents' familiarity with humanoid robots. Men reported greater familiarity than women, aligning with prior studies on the gender digital divide in technology adoption. Occupational status was also relevant: employed individuals and students demonstrated greater exposure to robotic technologies than retirees or unemployed respondents. Similarly, participants working in technology, healthcare, and education were more familiar with humanoid robots than those in agriculture, culture, or public administration. These findings confirm that familiarity is shaped by both gendered socialization patterns and professional exposure. Previous studies have argued that technology-intensive work environments act as facilitators of awareness and practical experience with advanced technologies (Pelau et al., 2021; Law et al., 2021).

- **RQ4–RQ5: Comfort with humanoid robots**

Both the field of work and marital status were significantly associated with comfort levels in interacting with humanoid robots. Respondents from technology and healthcare reported higher comfort, reflecting alignment with professional experience. Interestingly, marital status mattered: single respondents tended to be more comfortable with the idea of robotic assistance at home, while married respondents and those with families expressed slightly more reservations. This pattern resonates with Broadbent et al. (2009), who found that household context influences perceptions of healthcare robots. Comfort is not only a function of technological exposure but also of domestic responsibilities and expectations.

- **RQ6–RQ8: Acceptance and purchase intention**

The results indicate that gender, age, and income shape acceptance and intention to purchase humanoid robots. Men reported higher levels of acceptance, consistent with earlier findings that men are more likely to embrace novel technologies (Venkatesh & Morris, 2000). Age differences followed expected patterns: younger respondents showed greater willingness to purchase humanoid robots, consistent with studies on generational openness to innovation (Czaja et al., 2006; Baisch et al., 2017). Income

was also a significant factor, with higher-income respondents more willing to consider purchasing robots, aligning with theories of affordability and willingness to invest (Parasuraman & Colby, 2015). Together, these results suggest that acceptance and purchase intention are driven by socio-economic capital and generational openness, while gender differences persist as moderating factors.

The overall findings demonstrate that sociodemographic characteristics play a non-negligible role in shaping people's acceptance of humanoid robots. While the effect sizes are modest, they are consistent across multiple dimensions: familiarity, comfort, acceptance, and purchase intention.

From a theoretical standpoint, the results align with both technology acceptance theories (Davis, 1989; King & He, 2006; Xiao & Goulias, 2022) and human - robot interaction research (Nomura et al., 2006; Nomura et al., 2008; Kiesler et al., 2008). They reinforce the view that demographic segmentation provides a valuable lens through which to understand the diffusion of new technologies in society.

From a practical perspective, the findings imply that targeted communication and market strategies are needed for Romanian consumers and beyond. For example:

- **Women and older respondents** may require more tailored educational campaigns to reduce unfamiliarity and enhance comfort.
- **Professionals in traditional sectors** may benefit from exposure programs demonstrating practical applications of robots.
- **Higher-income and younger groups** represent early adopters, who may drive initial market uptake.

The chi-square tests not only identified significant relationships between demographic variables and respondents' familiarity and comfort with humanoid robots, but also enabled the evaluation of the strength of these associations through Cramer's V coefficients. According to the conventional thresholds proposed by Cohen (1988), values around 0.10 can be interpreted as indicating a small effect size, 0.30 as medium, and 0.50 as large. These benchmarks are widely applied in the behavioral and social sciences when interpreting associations between categorical variables (Cohen, 1988; Ellis, 2010).

Taken together, interpretations of effect sizes reinforce the conclusion that demographics exert small but non-negligible influences on perceptions of humanoid robots. This highlights the importance of integrating socio-demographic indicators with psychological and contextual variables in order to build a more comprehensive model of robot acceptance (table no. 2).

Table no. 2. Interpretation of Cramer's V effect sizes

Cramer's V value	Cohen's benchmark (Cohen, 1988)	Interpretation in this study
0.10	Small effect	Familiarity with robots by education, income → weak but relevant association
0.11–0.13	Small effect	Comfort with robots by marital status and living environment → modest influence
0.14–0.15	Small effect (approaching medium)	Occupational status → familiarity and comfort → notable differentiator

0.17–0.19	Small-to-moderate effect	Field of activity → strongest predictor of both familiarity and comfort
0.30	Medium effect (benchmark)	Not reached in this study
0.50	Large effect (benchmark)	Not reached in this study

Source: author's contribution

Although the effect sizes identified in this study remain within the “small” range according to Cohen’s benchmarks, they nonetheless carry practical significance for market segmentation and consumer targeting. In applied contexts such as technology adoption and marketing, even small differences across demographic groups can be leveraged to design more effective communication strategies, pilot programs, and product positioning (Ferguson, 2009). For example, knowing that professionals in technology-related fields exhibit slightly higher familiarity and comfort with robots provides companies with a strategic entry point for early adoption, which can later diffuse to broader consumer segments through social influence and demonstration effects (Rogers, 2003). Thus, while statistically modest, these associations contribute valuable insights into the pathways through which humanoid robots may gradually gain acceptance in society.

The results of this study can be situated within the broader literature on consumer adoption of humanoid robots and related technologies. The associations identified between demographic variables and perceptions of robots are consistent with a growing body of evidence that shows sociodemographic segmentation influences attitudes toward emerging technologies.

First, the finding that gender is significantly associated with both familiarity and acceptance of humanoid robots echoes earlier work on the gender gap in technology adoption. Gefen and Straub (1997) documented systematic differences in how men and women perceive the usefulness and ease of use of information systems, with men generally exhibiting higher adoption intentions. More recently, Song and Kim (2022) found that male respondents reported stronger perceptions of trust and social presence in interactions with humanoid robots, which, in turn, predicted a greater willingness to adopt them. The present study’s results confirm that such gendered differences extend to domestic robots, where men were more likely to express acceptance and purchase intention.

Second, the relationship between age and adoption intention aligns with well-established patterns in innovation research. Younger respondents in this study demonstrated greater willingness to purchase humanoid robots, consistent with Baisch et al. (2017) and De Jong et al. (2024), who observed that older adults often experience greater anxiety and lower self-efficacy regarding new technologies. Similarly, Venkatesh et al. (2012) emphasized generational differences in technology acceptance, noting that younger cohorts typically display higher behavioral intentions in response to perceived usefulness and ease of use. The current findings thus reinforce the notion that

age is a persistent determinant of openness to innovation, particularly in contexts involving sophisticated technologies such as humanoid robots.

Third, the significant effects of occupational status and field of activity are in line with prior research linking professional exposure to familiarity and comfort with robots. Law et al. (2021) highlighted that individuals with prior experience in technology-intensive environments reported greater comfort with humanoid robots. Similarly, Pelau et al. (2021) argued that occupational context is a key determinant of technological familiarity, as employees in sectors such as IT, healthcare, and education are regularly exposed to automation and artificial intelligence tools. The present study mirrors these findings, showing that respondents in technology-related and service-oriented sectors reported higher familiarity and comfort levels than those in agriculture, culture, or public administration.

In the context of humanoid robots, higher-income respondents in this study were more willing to consider purchase, reflecting the interplay between economic capacity and willingness to invest in novel products. These findings parallel broader consumer research showing that income moderates adoption by shaping perceptions of affordability and relative advantage (Parasuraman and Colby, 2015).

Interestingly, the present study adds nuance to prior research by showing that marital status shapes comfort with robots, an aspect that is less frequently examined in the literature. Single respondents were more comfortable with the idea of robotic assistance in domestic settings compared to married respondents. This result resonates with the study of Mende et al. (2019). Married respondents may evaluate robots not only in terms of personal utility but also in relation to family safety and privacy concerns, leading to more cautious attitudes.

Taken together, these findings confirm the external validity of previous studies while extending them by examining a broader range of sociodemographic variables within a single model. The study demonstrates that, although the statistical effects are modest, demographic factors consistently shape familiarity, comfort, and adoption intentions. This suggests that future research should further integrate demographic insights with psychological constructs (such as trust, anthropomorphism, and perceived usefulness) to develop richer explanatory models of robot acceptance. Moreover, the results highlight the importance of examining cultural and contextual factors—such as marital status or domestic environment—which may be underexplored in international literature but prove relevant in shaping attitudes toward domestic robotics. The study results reflect the specific characteristics of the Romanian context.

The exploratory nature of this study means that findings should be interpreted with caution. The non-probabilistic sampling design limits generalizability, and chi-square tests capture only associations, not causality. Despite their small magnitude, the observed effects are meaningful in applied contexts such as market segmentation, where incremental differences across demographic groups can inform targeted strategies. However, the results provide valuable insights into how sociodemographic segmentation influences consumer attitudes toward humanoid robots, which can inform both academic debate and industry practice.

Conclusions

Based on a heterogeneous Romanian consumer sample, this study illuminates the determinants and barriers to humanoid robot acceptance across domestic environments. This confirms the relevance of demographic factors as moderators in UTAUT and further demonstrates that gender, age, income, marital status, and occupation actively structure familiarity, comfort, and intention to adopt the technology.

Practically, the findings provide insights to multiple stakeholders. Designers are advised to calibrate anthropomorphic characteristics to make them more comfortable without generating resistance. Marketers should consider a segmented marketing with demographically targeted communications. Businesses can consider phased pricing models that align with their income-based acceptance patterns, and policymakers can foster an environment of trust through regulation and public outreach. Altogether, these policies could contribute to the peaceful, inclusive, and responsible diffusion of humanoid robots in everyday life.

However, this study has several limitations that should be recognized. First, non-probability sampling limits the generalizability of the findings. The sample composition may reflect biases typical of online surveys, with an overrepresentation of younger and more educated respondents. Secondly, a cross-sectional design measures perceptions only at a single point in time and does not allow for evaluating changes in attitudes as exposure to humanoid robots increases. Thirdly, the analysis relied on bivariate associations without testing more complex multivariate models (e.g., logistic regression or SEM). The use of bivariate analyses precludes the study of interactions among the demographic variables.

Future studies need to overcome these challenges by using probability-based sampling, longitudinal designs, multivariate methods, or experimental and qualitative methods to capture changes in attitudes. Additionally, expanding the analysis to include psychographic variables (e.g., openness to innovation, risk perception) could enrich the understanding of consumer adoption. Finally, integrating qualitative approaches (focus groups, interviews) may provide deeper insights into the nuances of comfort and acceptance.

References

- [1] Baisch, S., Kolling, T., Schall, A. et al., 2017. Acceptance of Social Robots by Elder People: Does Psychosocial Functioning Matter?. *Int J of Soc Robotics*, 9, pp. 293–307. <https://doi.org/10.1007/s12369-016-0392-5>
- [2] Baker, R. et al., 2013. Summary Report of the AAPOR Task Force on Non-probability Sampling. *Journal of Survey Statistics and Methodology*, 1(2), pp. 90–143. <https://doi.org/10.1093/jssam/smt008>
- [3] Broadbent, E., Stafford, R., MacDonald, B., 2009. Acceptance of Healthcare Robots for the Older Population: Review and Future Directions. *International Journal of Social Robotics*, 1(4), pp. 319–330. <https://doi.org/10.1007/s12369-009-0030-6>
- [4] Chen, X., Jiang, L., Zhou, Z., Li, D., 2025. Impact of perceived ease of use and perceived usefulness of humanoid robots on students' intention to use. *Acta Psychologica*, 258, 105217. <https://doi.org/10.1016/j.actpsy.2025.105217>

[5] Cohen, J., 1988. *Statistical power analysis for the behavioral sciences*. 2nd ed. Hillsdale, NJ: Lawrence Erlbaum Associates.

[6] Conner, M., McEachan, R., Lawton, R., Gardner, P., 2017. Applying the reasoned action approach to understanding health protection and health risk behaviors. *Social Science & Medicine*, 195, pp. 140–148. <https://doi.org/10.1016/j.socscimed.2017.10.022>

[7] Cooper, J., 2006. The digital divide: The special case of gender. *Journal of Computer Assisted Learning*, 22(5), pp. 320–334. <https://doi.org/10.1111/j.1365-2729.2006.00185.x>

[8] Czaja, S.J., Charness, N., Fisk, A.D., Hertzog, C., Nair, S.N., Rogers, W.A., Sharit, J., 2006. Factors predicting the use of technology: Findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and Aging*, 21(2), pp. 333–352. <https://doi.org/10.1037/0882-7974.21.2.333>

[9] Davis, F. D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), pp. 319-340.

[10] De Graaf, M., Ben Allouch, S., Van Dijk, J., 2017. Why do they refuse to use my robot? Reasons for non-use derived from a long-term home study, In: *Proceedings of ACM/IEEE international conference on human-robot interaction*. Vienna, Austria, 6 - 9 March 2017. Association for Computing Machinery: New York, United States (pp. 224-233). <https://doi.org/10.1145/2909824.3020236>

[11] De Jong, C., Peter, J., Kühne, R., Barco, A., 2024. Children's acceptance of a domestic social robot: how it evolves over time. *ACM Transactions on Human-Robot Interaction*, 13(2), pp. 1-20. <https://doi.org/10.1145/3638066>

[12] Ellis, P.D., 2010. *The essential guide to effect sizes: Statistical power, meta-analysis, and the interpretation of research results*. Cambridge: Cambridge University Press.

[13] Ferguson, C.J., 2009. An effect size primer: A guide for clinicians and researchers. *Professional Psychology: Research and Practice*, 40(5), pp. 532–538.

[14] Fink, J., 2012. Anthropomorphism and Human Likeness in the Design of Robots and Human-Robot Interaction, In: Ge, S.S., Khatib, O., Cabibihan, J.J., Simmons, R., Williams, M.A. (eds), *International Conference on Social Robotics 2012*. Chengdu, China, 29 - 31 October 2012, Lecture Notes in Computer Science, vol 7621 Springer: Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-34103-8_20

[15] Gefen, D., Straub, D. W., 1997. Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS quarterly*, pp. 389-400.

[16] Kiesler, S., Powers, A., Fussell, S. R., Torrey, C., 2008. Anthropomorphic interactions with a robot and robot-like agent. *Social cognition*, 26(2), pp.169-181. <https://doi.org/10.1521/soco.2008.26.2.169>

[17] Kim, M., 2025. Adoption of Home Service Robots: Exploring Household Differences in Perceived Usefulness, In: *IEEE Access*, vol. 13, pp. 64737-64749. <https://doi.org/10.1109/ACCESS.2025.3559060>

[18] King, W. R., He, J., 2006. A meta-analysis of the technology acceptance model. *Information & Management*, 43(6), pp. 740-755. <https://doi.org/10.1016/j.im.2006.05.003>

[19] Law, T., Chita-Tegmark, M., Scheutz, M., 2021. The interplay between emotional intelligence, trust, and gender in human–robot interaction: A vignette-based study. *International Journal of Social Robotics*, 13(2), pp. 297–309.

[20] Mahdi, H., Akgun, S. A., Saleh, S., Dautenhahn, K., 2022. A survey on the design and evolution of social robots—Past, present and future. *Robotics and Autonomous Systems*, 156, 104193. <https://doi.org/10.1016/j.robot.2022.104193>

[21] Makwana, D., Engineer, A., Dabhi, R., Chudasama, J., 2023. Sampling methods in research: A review. *International Journal of Trend in Scientific Research and Development*, 7(3), pp. 762–768.

[22] Marikyan, D., Papagiannidis, S., 2025. *Unified Theory of Acceptance and Use of Technology: A review*. [Online] In: S. Papagiannidis (Ed), TheoryHub Book. Available at <https://open.ncl.ac.uk/> ISBN: 9781739604400

[23] Mende, M., Scott, M. L., van Doorn, J., Grewal, D., Shanks, I., 2019. Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses. *Journal of Marketing Research*, 56(4), pp. 535–556. <https://doi.org/10.1177/0022243718822827>

[24] Momani, A. M., 2020. The unified theory of acceptance and use of technology: A new approach in technology acceptance. *International Journal of Sociotechnology and Knowledge Development (IJSKD)*, 12(3), pp. 79–98.

[25] Nomura, T., Kanda, T., Suzuki, T., 2006. Experimental investigation into influence of negative attitudes toward robots on human–robot interaction. *AI & Society*, 20(2), pp. 138–150. <https://doi.org/10.1007/s00146-005-0012-7>

[26] Nomura T, Kanda T, Suzuki T, et al., 2008. Prediction of human behavior in human-robot interaction using psychological scales for anxiety and negative attitudes toward robots. *IEEE Trans Robot*, 24, pp.442–451.

[27] Pace, R.K., 2021. Nonprobability sampling for applied research in economics and management. *International Journal of Quantitative and Qualitative Research Methods*, Vol.9, No.2, pp.1-15.

[28] Papadopoulos, I., Koulouglioti, C., Lazzarino, R., Ali, S., 2020. Enablers and barriers to the implementation of socially assistive humanoid robots in health and social care: a systematic review. *BMJ open*, 10(1), pp. 1-13. <https://doi.org/10.1136/bmjopen-2019-033096>

[29] Parasuraman, A., Colby, C. L., 2015. An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, 18(1), pp. 59–74. <https://doi.org/10.1177/1094670514539730>

[30] Park, S., Whang, M., 2022. Empathy in Human–Robot Interaction: Designing for Social Robots. *International Journal of Environmental Research and Public Health*, 19(3), 1889. <https://doi.org/10.3390/ijerph19031889>

[31] Pelau, C., Ene, I., Pop, M.I., 2021. Impactul inteligenței artificiale și al roboților asupra consumatorilor și abilităților umane. *Amfiteatru Economic*, 23(56), pp. 33–45. <https://doi.org/10.24818/EA/2021/56/33>

[32] Premathilake, G.W., Li, H., 2024. Users' responses to humanoid social robots: A social response view. *Telematics and Informatics*, 91, p.102146. <https://doi.org/10.1016/j.tele.2024.102146>

[33] Rogers, E.M., 2003. *Diffusion of innovations*. 5th ed. New York: Free Press.

[34] Schneiders, E., Papachristos E., van Berkel N., Jacobsen, R. M., 2023. Briefly Entertaining but Pointless: Perceived Benefits & Risks of Social Robots in the Home. In: Extended Abstracts of the *CHI Conference on Human Factors in Computing Systems (CHI EA '23)*. Hamburg, Germany, 23 – 28 April 2023. Association for Computing Machinery: New York, United States, Article 61 (pp. 1–6). <https://doi.org/10.1145/3544549.3585696>

[35] Song, C.S., Kim, Y.K., 2022. The role of the human-robot interaction in consumers' acceptance of humanoid retail service robots. *Journal of Business Research*, 146, pp. 489–503. <https://doi.org/10.1016/j.jbusres.2022.03.087>

[36] Spaccatini, F., Corlito, G., Sacchi, S., 2023. New dyads? The effect of social robots' anthropomorphization on empathy towards human beings. *Computers in Human Behavior*, 146, 107821. <https://doi.org/10.1016/j.chb.2023.107821>

[37] van Pinxteren, M.M.E., Wetzels, R., Rüger, J., Pluymakers, M., Wetzels, M., 2019. Trust in humanoid robots: implications for services marketing. *Journal of Services Marketing*, 33(4), pp: 507–518. <https://doi.org/10.1108/JSM-01-2018-0045>

[38] Venkatesh, V., Davis, F. D., 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, 46(2), pp: 186-204. <https://doi.org/10.1287/mnsc.46.2.186.11926>

[39] Venkatesh, V., Morris, M.G., 2000. Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, 24(1), pp. 115–139. <https://doi.org/10.2307/3250981>

[40] Venkatesh, V., Morris, M. G., Davis, G. B., Davis, F. D., 2003. User acceptance of information technology: Toward a unified view. *MIS quarterly*, pp. 425-478.

[41] Venkatesh, V., Thong, J.Y.L., Xu, X., 2012. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), pp. 157–178. <https://doi.org/10.2307/41410412>

[42] Xiao, J., Goulias, K. G., 2022. Perceived usefulness and intentions to adopt autonomous vehicles. *Transportation research part A: policy and practice*, 161, pp.170-185, <https://doi.org/10.1016/j.tra.2022.05.007>

[43] Wu, Y. H., Wrobel, J., Cornuet, M., Kerhervé, H., Damnée, S., Rigaud, A.S., 2014. Acceptance of an assistive robot in older adults: a mixed-method study of human–robot interaction over a 1-month period in the Living Lab setting. *Clinical Interventions in Aging*, 9, 801–811. <https://doi.org/10.2147/CIA.S56435>