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The Netherlands

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User Gratifications and Gender Patterns

in ChatGPT Adoption

Denise Wiharnadi
S3323099

Supervisors:
Dr. N. Amat Lefort & Dr. T. Verhoef

BACHELOR THESIS

Leiden Institute of Advanced Computer Science (LIACS)
www.liacs.leidenuniv.nl

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Abstract

Generative AI Chatbots such as ChatGPT have become widely adopted and continue to shape how people interact with digital systems. To gain new insights into the user experience for such tools, this study applies the Uses and Gratifications (U&G) theory. The study examines how five types of gratification influence user satisfaction and loyalty to ChatGPT. These types include instrumental, usability, trust, control and safety, and identity-related gratification. Data were collected through an online survey with 411 ChatGPT users. The relationships between the gratification types, satisfaction and loyalty were tested with Structural Equation Modeling. A multigroup analysis further explored whether these relationships vary across gender. The results show that instrumental and usability gratification are the strongest predictors of satisfaction for both men and women. Trust only had a significant effect for women, while control and safety were only significant for men. Identity-related gratification did not have a significant impact on satisfaction for either group. Satisfaction was also found to strongly predict user loyalty. Although some gender-based differences were observed, the multigroup analysis did not show statistical significance. The findings support the relevance of traditional U&G types in the context of modern technology and generative AI, while newer gratification types may require clearer definitions and measurement. The study also provides practical implications for improving chatbot design in terms of usability, personalization, and user control.

Keywords: Generative AI, ChatGPT, Uses and Gratifications Theory, Gender Differences, User Satisfaction

Contents

1 Introduction

The role of artificial intelligence (AI) in everyday life is growing rapidly. Generative AI chatbots, such as ChatGPT, are powered by large language models (LLMs) that generate text based on user input. While often used for information retrieval, they are also designed to hold conversations with users and adapt to what people say [20]. As these systems grow more advanced, they seem to gain more purposes [60]. Some people use generative AI chatbots for quick answers to practical questions, while others are curious if AI can really understand them or offer advice [46]. The way people interact with AI is not only shaped by their personal goals but also by underlying social patterns that have influence on their technology use. Prior research has shown that large language models may reflect and reproduce such social patterns, including gender based assumptions or stereotypes [38].

As AI usage becomes more normalized in society, it also reveals deeper differences in how people from different demographics access and use technology. The digital divide is commonly defined as a gap between people who do and do not have access to forms of information and communication technology, especially access to the internet [55]. The digital divide first started as the issue of certain demographics having limited physical access to technology, but now also shows inequalities in how users interact with technology and how much they benefit from it [30] For example, a survey by Friemel [12] shows that digital skills vary significantly for different age groups. Gender differences in the use of technology have also been widely reported. Male users are often more confident using digital tools, even when skill levels are similar [59]. On the other hand, women may face more barriers related to trust or emotional engagement when dealing with AI [31]. This suggests that demographic factors like gender have influence on how people use AI, as well as how satisfied they are with it.

Building on the Uses and Gratifications (U&G) theory, this research aims to explore how users engage with generative AI chatbots to fulfill specific needs. This theory sees users as active participants who choose the forms of media they consume based on these needs [21]. These needs can be functional, emotional or social. For example users might choose certain media for entertainment purposes or too express themselves [45]. U&G theory has evolved over the years to keep up with technology and digital platforms [48]. It now also accounts elements such as personalization and interactivity, which have become more important for users in recent media [45, 52]. This is especially relevant for generative AI, as it is often praised for its speed and convenience. At the same time, it is sometimes criticized for being unpredictable or inaccurate, depending on the user's expectations [49]. While U&G theory was first used to study traditional media such as radio or television, more recent work shows it can also be applied to AI systems [36].

The goal of this thesis is to explore which types of user gratification are most important for users of generative AI chatbots, in order to provide a better understanding of how people experience AI. The study examines what leads to user satisfaction and loyalty. The types of gratification considered include practical value, trust in information, ease of use, personalization, and control over data and privacy. The study also looks at possible differences in how men and women value these factors, which sheds light on whether current technologies serve all users equally. This study focuses on ChatGPT as a representative example of a generative AI chatbot.

The study aims to answer the following research question:

To what extent do different types of user gratifications influence satisfaction with ChatGPT, and do these relationships differ between men and women?

2 Theoretical Background

2.1 The Digital Divide

The digital divide refers to the differences in how individuals are able to access and use technologies across demographic groups. At first it only concerned the disparities in people's access to digital devices [55]. Over time, this divide has evolved and expanded to deeper levels [7]. Even when people possess the same tools, there are differences in digital skills, frequency of technology use, and the ability to use technology. To add to that, even when their internet use patterns are similar, users can experience gaps in their societal benefits [27]. These deeper levels of inequality show that only aiming to ensure access is not enough to bridge the divide [2]

Gender plays a large role in the digital divide. There is still a gap in access between men and women in parts of the world, mainly due to sociocultural factors [3] Research shows that men and women often experience digital environments in different ways. Even when their actual abilities are on similar levels, women are more likely to report lower confidence in using technology than men [59]. This does not always have to do with actual skill, but is also about how comfortable people feel in digital spaces. This confidence is often shaped by wider stereotypes about gender and competence with technology, as well as STEM in general [47]. It has also been shown that when stereotypes about girls being less interested in computer science are endorsed around children, the girls who hear this are inclined to be less connected to the field [31].

These gender differences can often influence how people use digital tools. For example, men seem to focus more on efficiency and the practical value of technological tools [53]. This shapes the kinds of technologies people prefer, but also how much value they get out of using them. In the context of AI, patterns of the digital divide become even more visible. Some studies show that generative AI (GenAI) can widen gaps in education, jobs, and healthcare [6, 1].There were cases found where large language models reflect gender stereotypes [38], which may affect how users relate to the technology. This could result in lower trust and engagement from women, adding another layer to the gender digital divide.

2.2 Uses and Gratifications Theory

This study relies on the framework of the Uses and Gratifications (U&G) theory to understand why people use generative AI chatbots, such as ChatGPT. This theory was developed by Katz, Blumler, and Gurevitch based on the idea that people actively choose media that fits their personal needs

and goals [22]. This theory sees users as active participants who choose media to satisfy specific needs, instead of them just passively consuming content [44]. They are searching for tools and platforms that help them do something specific or feel a certain way. Over the years, the theory has developed to account for how people use interactive and digital platforms. This theory has been extended to modern media as well [45], especially as users now have more choice and freedom in how they engage with technology.

This theory has also proven useful for providing new insights into AI. Generative AI chatbots are not just information sources. They are also tools that can be shaped by users' input. Users were found to not only engage with AI chatbots for information but also for entertainment, social interaction, and technological appeal [9]. People now expect media to be more interactive and adaptive [52].They want to have control and prefer technology that responds to their preferences. Generative AI chatbots can tend to a lot of these needs. The kind of gratification people get from using it depends on what they need from the tool at that moment. Application of the U&G framework to chatbots showed that when the needs for convenience and enjoyment were met, users had more positive attitudes [29].

2.3 Gendered Patterns in Media Gratification

One angle in Uses and Gratifications research is the role of demographic differences, with gender standing out as especially important. Over the years, studies have repeatedly shown that men and women do not use media in the same way. Men were found more likely to look for practical benefits when using media, while women tend to place more value on relational and emotional experiences [25]. These differences have not disappeared with the rise of digital technology. Research showed that women still prefer media that allows for emotional connection and communication, whereas men remain more interested in productivity and information gathering [37]. Another study on text messaging among young adults also showed significant differences in how men and women prioritize and respond to specific gratifications [16]. Although women tend to be more driven by social and emotional motivations and men by information, this can also vary across cultures [15, 24]. These studies highlight the value of gender as a lens to examine users' engagement with communication technologies through.

In the context of AI, these gender patterns are also apparent, however underexplored. A recent study on generative AI chatbots in higher education found that men used chatbots more often and for a wider range of tasks, focusing on efficiency. Women were more cautious and expressed concerns about trust among other things [35]. This is also in line with other research on how men tend to feel more familiar with AI than women, which could explain their higher confidence and usage [14]. While these are relevant and recent insights, there is still a notable gap in research on gendered differences in AI experiences. Even less is known on the insights that applying U&G theory might provide on this topic. Addressing this gap with empirical work contributes to understanding the dimensionality of user interactions with generative AI chatbots and similar emerging technologies.

3 Theoretical Framework

The U&G framework explains how people actively pursue certain forms of media to fulfill specific needs. Users make deliberate choices about which technologies to use, based on the types of gratification they hope to gain [44]. While initially the theory was developed for TV and radio [5], in recent years it has been applied to social media [58], and in a few cases it has already been applied to look into user behavior around generative AI chatbots [29].

This research builds on the U&G framework to explore how users interact with generative AI chatbots such as ChatGPT, focusing on the five gratification types described below. Each of these is assumed to contribute to user satisfaction, which in turn is expected to influence loyalty. This model reflects the idea that users actively engage with digital tools to meet specific needs. How well these needs are fulfilled shapes their overall experience. This study also examines whether the effect of these gratifications differ for men and women. Prior research suggests that men often focus more on instrumental benefits like efficiency, while women tend to place more emphasis on emotional trust and ease of use [56, 26]. To test these gendered differences in regards to user satisfaction with ChatGPT, a multi-group analysis is conducted. This method allows for a direct comparison of how each gratification type affects satisfaction for male and female users.

3.1 Gratification Types in the Context of AI

Throughout the years, the development of modern media has caused different types of gratification to be formulated. This research focuses on five types of gratification derived from U&G theory. Each of these gratifications is focused on a different motivation for using ChatGPT. Together, they aim to better understand how people experience ChatGPT and what drives them to use it. The hypotheses in this study propose that each of the five gratification types positively influences user satisfaction with ChatGPT. Additionally, it is expected that higher satisfaction will lead to increased user loyalty. The study also explores whether these relationships differ between men and women, as gender may influence how users engage with and evaluate digital technologies.

3.1.1 Instrumental Gratification

Users gain satisfaction when they accomplish tasks efficiently [13]. Within U&G theory, this is known as instrumental gratification. Users actively select tools that are useful and can save time [45, 61]. Generative AI chatbots such as ChatGPT meet this need directly. People use ChatGPT to quickly generate content or solve problems. A recent survey of early adopters, which also applied U&G theory, found that productivity was a leading reason for using generative AI [49]. ChatGPT fulfills instrumental gratification by enabling users to accomplish tasks with speed and ease. These kinds of results suggest that instrumental gratification is likely to play an important role in how users evaluate their experience with ChatGPT.

H1a: Instrumental gratification will have a significant positive influence on user satisfaction with

ChatGPT for men.
H1b: Instrumental gratification will have a significant positive influence on user satisfaction with ChatGPT for women.

Previous research has shown that men and women differ in how they experience instrumental gratification. Multiple surveys across continents show that men prioritize task efficiency and information-oriented gratifications more than women [15]. Women also seem to rate their own abilities in technical or STEM-related tasks lower, even when their performance is on the same level or better than men's [57]. These differences shape how users experience tools that are meant to improve efficiency. Men are more likely to feel empowered by such features and see them as rewarding, while women may feel less confident using them to their full potential. A Chinese study highlights how cultural norms around gender roles reinforce these differences and again shows girls having lower self-efficacy around technology [8]. These findings suggest that instrumental gratification may influence satisfaction in different ways for men and women.

H2: The relationship between instrumental gratification and satisfaction differs significantly between men and women.

3.1.2 Trust Gratification

Trust gratification ìs measured by the quality of information and knowledge users obtain. Users want accurate and trustworthy information. U&G research shows that people often seek media for learning or understanding [9]. Digital tools are now used for deeper comprehension, not just for browsing [52]. The gratification obtained from this is tied closely to trust in AI. ChatGPT's ability to provide reliable knowledge is a key part of its appeal and users continuously test its credibility when they ask questions. If the responses seem accurate, it builds trust and satisfaction [18]. Reducing bias or unclear answers in AI has shown to significantly improve trust [38]. Users need to believe the AI is a reliable source, especially for important tasks.

H3a: Trust gratification will have a significant positive influence on user satisfaction with ChatGPT for men.
H3b: Trust gratification will have a significant positive influence on user satisfaction with ChatGPT for women.

Gender differences in trust gratification have been consistently reported in media use and technology adoption. A study on trust in e-commerce found that trust was significantly more important for women than for men [4]. Neuroscience research has also added another layer by showing that the brain processes trust differently depending on gender, with women activating more brain regions related to trust evaluation than men [43]. Virtual community research supports this by showing that men and women respond to different cues for building trust. While men tend to place more value on high-quality content, women are more responsive to efforts that promote connection [39]. This aligns with U&G theory, which proposes that people seek gratifications that reflect their social roles and needs. These findings support the idea that trust gratification may influence satisfaction

differently across genders.

H4: The relationship between trust gratification and satisfaction differs significantly between men and women.

3.1.3 Usability Gratification

Usability gratification is the satisfaction users get from a system being easy and pleasant to use. When technology is intuitive and behaves in expected ways, users feel more in control. A user-friendly interface promotes longer lasting engagement [52]. The system itself becomes gratifying when it is convenient and takes little effort to use. ChatGPT has a conversational design that returns natural-sounding and well-structured outputs without delay. Ease of use is often mentioned as a key reason people continue using ChatGPT [60]. The system also replies in a manner that sometimes replicates human conversation. A study on the conversational agent Alexa revealed that personification of AI positively predicts satisfaction [40]. These factors all show that ChatGPT's usability is one of the gratifications users look for.

H5a: Usability gratification will have a significant positive influence on user satisfaction with ChatGPT for men.
H5b: Usability gratification will have a significant positive influence on user satisfaction with ChatGPT for women.

Gender differences in usability gratification are evident in how men and women evaluate interfaces and their ease of use. Usability research shows that women place more value on usability needs than men and that men and women have different expectations of usability features [17]. Another article on eye-tracking found that men and women focus on different parts of the same interface, with men drawn to maps and women paying more attention to text, search bars, and visual elements [32]. What users consider helpful or intuitive can vary by gender, which supports the idea that usability gratification is experienced differently.

H6: The relationship between usability gratification and satisfaction differs significantly between men and women.

3.1.4 Identity-related Gratification

Identity-related gratification comes from feeling that a system recognizes a user as an individual. One of the reasons people use digital platforms is to show their personality. U&G research has shown that social platforms can support self expression and that engagement grows when users feel that their identity is acknowledged [11]. Sundar and Limperos suggest that this sense of recognition comes from gratification based in agency, as users experience satisfaction when they can actively shape and direct their interaction [52]. Generative AI chatbots such as ChatGPT allow for such

personalization by providing different types of interactions. It can change its tone or response structure depending on the prompt. There is evidence that shows that when users see the AI reflecting their preferences, satisfaction increases [50]. Personalized responses can create a stronger connection to the tool, which in turn improves satisfaction.

H7a: Identity-related gratification will have a significant positive influence on user satisfaction with ChatGPT for men.
H7b: Identity-related gratification will have a significant positive influence on user satisfaction with ChatGPT for women.

Both U&G research and broader studies of online self-representation show that identity-related gratification presents itself differently in men and women. For example, young women often develop a stronger emotional connection to their phones than men. Technology helps them maintain a sense of independence while staying available to friends and family, thus allowing them a form of self-expression [16]. Another study of Facebook profiles found that men and women present themselves differently through their profile photos. Men seem to emphasize status and risk, while women highlight emotional expression in their pictures [51]. These disparities suggest that men and women use technology to fulfill distinct identity-related needs, which could lead to differences in user satisfaction depending on what kind of self-expression a platform allows.

H8: The relationship between identity-related gratification and satisfaction differs significantly between men and women.

3.1.5 Control and Safety Gratification

Control and safety gratification is rooted in the desire for users to be in charge when interacting with technology. Interactive media have introduced new expectations in this area [52]. With modern media becoming more responsive and personal, users now expect more than just basic functionality. They want systems that offer control and transparency over the interaction [34]. Perceived user control is revealed to be an important factor for customers using self-service technology [23], which shows how it can improve gratification. Unpredictability or lack of clarity can make users feel uneasy. Privacy-related behaviors are shown to be shaped by the way people use technology in specific contexts [42]. Their findings suggest that safety and control respond to the design and purpose of the platform. When users feel they can manage how data is used or how a system responds, they are more likely to trust the experience and continue using it.

H9a: Control and safety gratification will have a significant positive influence on user satisfaction with ChatGPT for men.
H9b: Control and safety gratification will have a significant positive influence on user satisfaction with ChatGPT for women.

Research on cyber security clearly shows that control and safety gratification is often not experienced in the same manner for men and women. One study shows women often perceive online tracking as

invasive and respond more strongly to it than men, although they take less measures for protection [33]. A second study on privacy attitudes of social media that applies U&G also suggests women are more likely to control privacy settings to maintain control [42]. These patterns show that women place more value on having control over how they are seen online and supports the idea that control and safety gratification influences satisfaction with ChatGPT differently for men and women.

H10: The relationship between control and safety gratification and satisfaction differs significantly between men and women.

3.1.6 User Satisfaction and Loyalty

User satisfaction plays a critical role in determining whether people stay loyal to generative AI chatbots. In the case of ChatGPT, a recent case study has shown that people are more likely to continue using the tool and recommend it to others when they are satisfied with the user experience [19]. Satisfaction strengthens the relationship between users and the platform. Based on this, user satisfaction is assumed to be a strong predictor of loyalty for both men and women.

H11a: User satisfaction will have a significant positive influence on user loyalty toward ChatGPT for men.
H11b: User satisfaction will have a significant positive influence on user loyalty toward ChatGPT for women.

3.2 Research Model

This study tests each of the relationships between the five types of gratification, user satisfaction, and loyalty. Each of the five gratification types is expected to influence user satisfaction, which in turn is assumed to affect loyalty. In addition to testing these direct effects, the model also examines if gender moderates the relationship between each gratification type and satisfaction. This makes it possible to examine whether men and women experience with ChatGPT in different ways. The diagram in figure 1 models all of these relationships.

Although the application of U&G theory to AI technologies is increasing, the interaction between gratification types and user satisfaction with generative AI chatbots has not been explored much yet. Gender differences have been even less covered in this context. This study fills that gap with a structured approach that links theory to measurable outcomes.

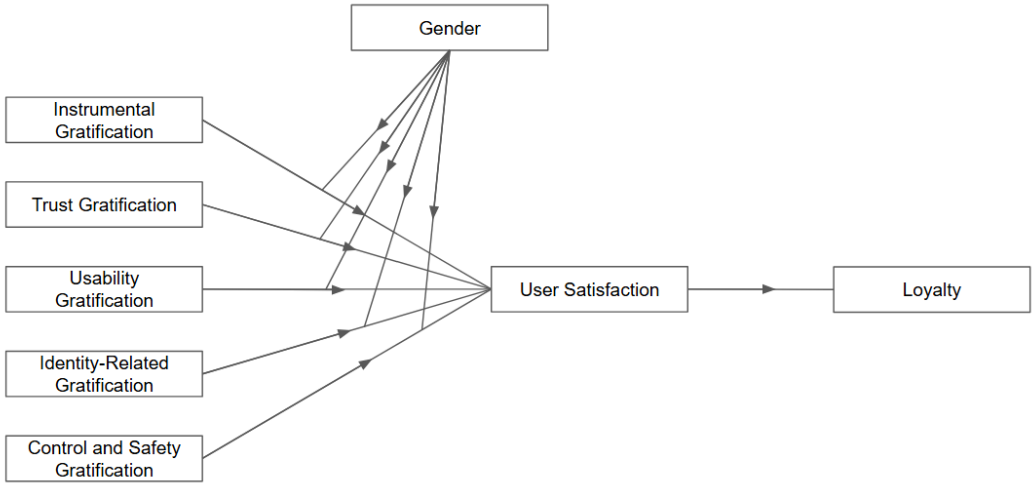

Figure 1: Model diagram showing the relationship between the gratifications, user satisfaction, and loyalty, with gender as a moderating variable.

4 Methodology

4.1 Research Design

This study uses a quantitative research design to explore how different types of user gratification relate to satisfaction with ChatGPT. An online survey was conducted to collect data for the analysis. The following describes the data exploration process, as well as the model that was built using Structural Equation Modeling (SEM) to test the hypotheses.

4.2 Participants and Data Collection

Data were collected using a paid online survey, where participation was voluntary and anonymous. The survey measured user experiences with ChatGPT across several dimensions. This study used a dataset derived from these same survey results [28]. All items were rated on a five-point Likert scale ranging from "strongly disagree" to "strongly agree". Respondents were required to have prior experience using ChatGPT to be included in the study. The final dataset consisted of 411 participants. There was an almost equal balance of gender, with 208 male and 203 female participants. It also included a mix of ages and education levels. Most respondents were between 26 and 45 years old. Users younger than 20 and older than 55 were the least represented. 45.5% of participants had completed university-level education, and 39.4% had obtained a Master's or PhD degree. Patterns in ChatGPT usage also differed. The largest group, 34.8%, uses it once per week. 18% of users reported using ChatGPT intensively every day, while 20.9% used it once per day. The rest only uses it in very few occasions. A clear overview of the participant demographics is presented in Table 1. All survey items on the demographic traits of the participants are listed in

Appendix A.

The participants were divided into two groups, male and female, to allow for a comparative analysis. This setup made it possible to find out whether certain types of gratification or satisfaction levels are experienced differently depending on gender.

Category	**Group**	**Frequency**	**Percentage**
Gender	Male	208	50.6%
	Female	203	49.4%
Age (years)	18–20	23	5.6%
	21–25	65	15.8%
	26–35	100	24.3%
	36–45	117	28.5%
	46–55	65	15.8%
	>55	41	9.9%
Education	Currently enrolled	10	2.4%
	Basic/prof. studies	52	12.7%
	University studies	187	45.5%
	Master's or PhD studies	162	39.4%
ChatGPT usage	Intensively every day	74	18.0%
	Once per day	86	20.9%
	Once per week	143	34.8%
	In very few occasions	108	26.3%

Table 1: Demographic overview of survey participants

4.3 Constructs and Survey Measures

The survey responses revealed five significant dimensions in how people experience ChatGPT. These dimensions were borrowed from the same study in which the dataset was originally developed [28]. They were identified through factor analysis and show where users' opinions and experiences cluster. Based on these findings, each of these five dimensions is mapped to a specific type of user gratification. This mapping makes it possible to test how each type of gratification influences user satisfaction. The survey dimensions are structured as follows, and the survey items that correspond to each dimension are listed in Appendix B:

- Efficiency (EFF1–EFF5):
  The efficiency questions measure how well ChatGPT helps users complete tasks and improve productivity. Efficiency is mapped to instrumental gratification because it reflects usefulness and completing tasks.
- Trust (TRU1–TRU4):
  The trust items assess accuracy and trust in ChatGPT's responses. It is mapped to trust gratification, as it focuses on user confidence in the provided information.

- Interface and Presentation (I&P1–I&P3):
  These questions evaluate ease of use and visual appeal of the platform. It is linked to usability gratification as it captures how intuitive and comfortable the user experience is.

- Personalization (PER1–PER3):
  The personalization dimension looks at whether ChatGPT adapts to user preferences and customizes responses. This is mapped to identity-related gratification as it measures if the system feels personal and responsive.

- Privacy and Security (P&S1–P&S4):
  These items measure perceived data privacy. This dimension is mapped to control and safety gratification, which highlights the importance of feeling safe and in control.

These five dimensions made it possible to measure how different user motivations might affect satisfaction. The survey also included one item for overall satisfaction (SAT) and three items on loyalty (LOY1–LOY3), which ask if users plan to continue using ChatGPT and whether they would recommend it to others. Table 2 clearly shows which survey dimensions are mapped to which gratification types.

Gratification Type	**Survey Dimension**
Instrumental	Efficiency
Trust	Trust
Usability	Interface & Presentation
Identity-Related	Personalization
Control & Safety	Privacy & Security

Table 2: Operationalization of gratification constructs.

4.4 Structural Model Assessment

The Confirmatory Factor Analysis (CFA) for the model had already been conducted before the research, which revealed the five significant dimensions from the survey. Following this, the structural model was built to test the hypothesized relationships. All five gratification types were placed as direct predictors of satisfaction, and satisfaction was modeled as a predictor of loyalty. Model fit was evaluated using the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the chi-square to degrees of freedom (χ^2/df). These indices show how well the model represents the data.

To explore gender differences in how gratification types influence satisfaction, a multigroup SEM was conducted. At first, the model was tested separately for male and female users without using any equality constraints. Estimating the model this way gives a general overview the strength of the relationships. This also made it possible to make initial observations on which gratification types might have stronger or weaker effects depending on gender. Figure 2 shows the complete model, built in IBM SPSS AMOS 27.

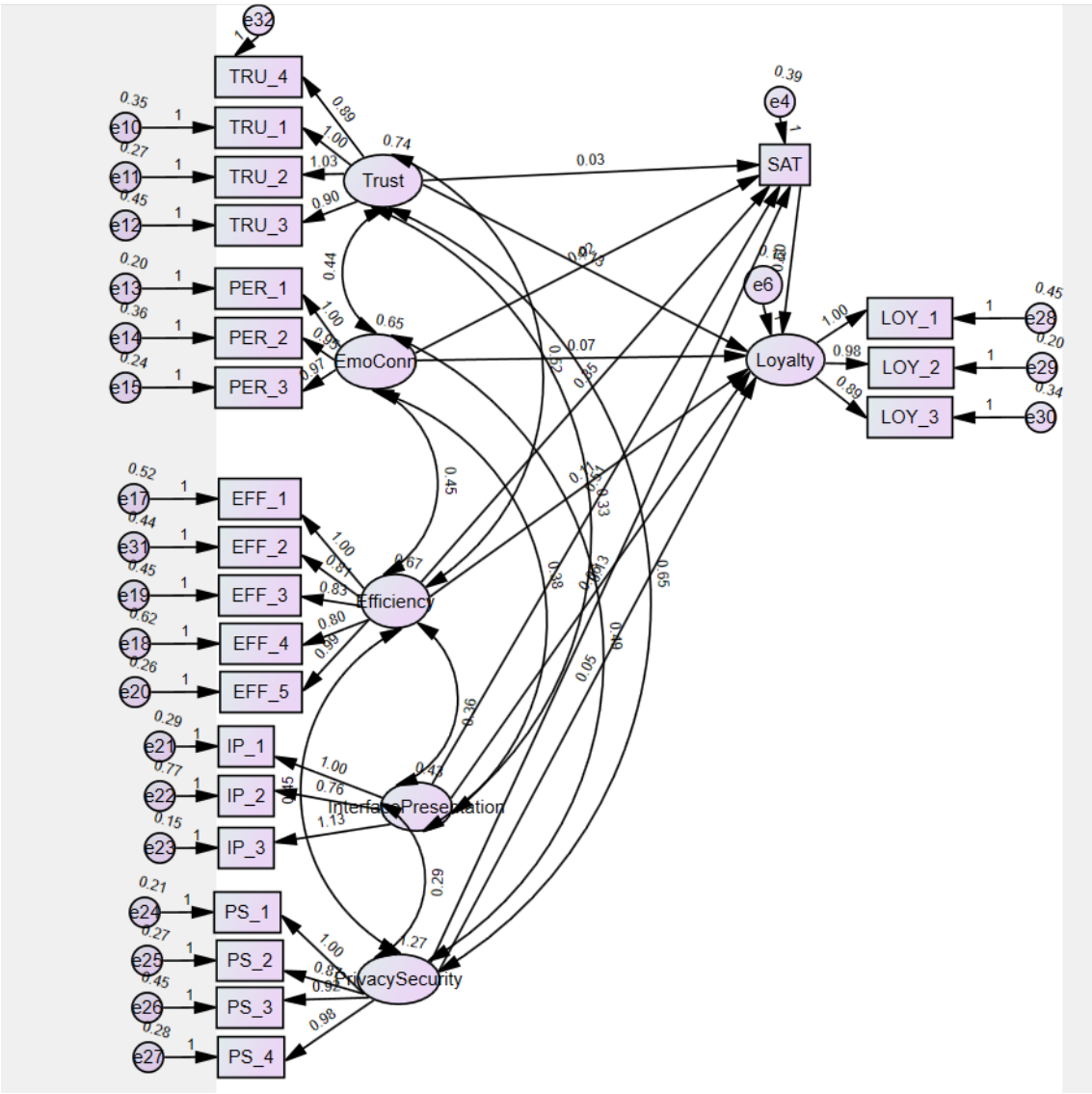

Figure 2: Structural equation model (SEM) in AMOS showing relationships between gratification types, satisfaction, and loyalty.

4.5 Multigroup SEM with Constraints

The final phase of the modeling was to examine whether the relationships between the gratification types and user satisfaction differ significantly between men and women. To do this, a multigroup Structural Equation Modeling (SEM) approach with equality constraints was applied. This type of analysis allows for a direct comparison of the model structure across different groups to see whether the same factors influence satisfaction in the same way.

Multigroup SEM is very useful for assessing if relationships between constructs in the model are consistent across groups. The first step involved building a version of the model where male and

female participants were analyzed separately, without any constraints being used. This unconstrained model served as a baseline and gave insight into the way each gratification type influenced satisfaction in each group. These results already showed some differences in the strength and significance of the paths. However, this does not proof statistical significance.

To determine if the baseline differences were actually statistically significant, the same model was estimated for both male and female participants with constraints placed on the paths. Each path from survey dimension to satisfaction was constrained one at a time to be equal for the two groups. The constrained model was then compared to the first unconstrained version. If the fit of the constrained model had become significantly worse ($p < 0.05$), it meant that that specific path was not equal across groups. This indicates a significant gender difference in how that gratification type influences satisfaction.

The changes in model fit were assessed using chi-square difference testing. This is a technique for evaluating structural invariance. A significant increase in the chi-square value is an indication that constraining a path has worsened the model. This result suggests that gender plays a role in how that particular gratification influences satisfaction. On the other hand, if the model fit stayed roughly the same, it would suggest that the relationship between the gratification and satisfaction holds equally across groups.

In the analysis, none of the constrained paths exceeded the threshold for significance. This means that even though some types of gratification appeared stronger for one gender in the baseline model, the differences were not large enough to be statistically significant when tested. The full results are shown in Section 5.3.

5 Results

5.1 Baseline Model Fit and Interpretation

The baseline multigroup model, estimated without constraints, showed excellent fit across both groups. The CMIN/DF was 1.895. The CFI was .947 and the RMSEA was .033, which all show a strong model fit. The PCLOSE value was 1.000, which indicates that there was no significant difference between the model and the dataset. Together, this confirms that the model is statistically acceptable and that the hypothesized relationships hold well in both gender groups. An overview of the core model fit statistics is provided in Table 3.

5.2 Structural Path Estimates

The structural path estimates for male and female participants were examined separately by using standardized regression weights. This way, the strengths and significance of each hypothesized relationship within the model can be compared. Table 4 shows all of the paths as the relationships

Fit Index	Value
χ^2/DF (CMIN/DF)	1.895
Comparative Fit Index (CFI)	0.947
Tucker-Lewis Index (TLI)	0.936
Root Mean Square Error of Approximation (RMSEA)	0.033
PCLOSE	1.000

Table 3: Model fit indices

they represent between each form of gratification and satisfaction. The effect of satisfaction on loyalty is also shown.

Relationship	Estimate	p-value	Hyp.	Supported
Instrumental gratification → Satisfaction (men)	0.313	.003	H1a	Yes
Instrumental gratification → Satisfaction (women)	0.273	.004	H1b	Yes
Trust gratification → Satisfaction (men)	0.026	0.802	H3a	No
Trust gratification → Satisfaction (women)	0.171	0.042	H3b	Yes
Usability gratification → Satisfaction (men)	0.359	$< .001$	H5a	Yes
Usability gratification → Satisfaction (women)	0.573	$< .001$	H5b	Yes
Identity-related gratification → Satisfaction (men)	0.018	0.120	H7a	No
Identity-related gratification → Satisfaction (women)	-0.135	0.120	H7b	No
Control & Safety gratification → Satisfaction (men)	0.154	0.043	H9a	Yes
Control & Safety gratification → Satisfaction (women)	0.036	0.532	H9b	No
Satisfaction → Loyalty (men)	0.633	$< .001$	H11a	Yes
Satisfaction → Loyalty (women)	0.364	$< .001$	H11b	Yes

Table 4: Multigroup SEM Results: Path Estimates and Hypothesis Tests

The results show that instrumental gratification clearly contributes to satisfaction for both men and women. For men, the relationship was moderately strong ($\beta = 0.313$, $p = .003$), and for women it was slightly lower but still significant ($\beta = 0.273$, $p = .004$). So, when users feel ChatGPT is efficient and helps them complete tasks, they tend to be more satisfied. This supports both H1a and H1b.

Trust, on the other hand, only mattered for women. For female users, trust in the information from ChatGPT had a significant effect on satisfaction ($\beta = 0.171$, $p = 0.042$). For men, the effect was close to zero and was not significant ($\beta = 0.026$, $p = 0.802$). This supports H2b, but not H2a. So trust in the quality and accuracy of ChatGPT's responses plays a bigger role for women, while it does not significantly affect satisfaction for men.

Similar to instrumental gratification, usability gratification was a strong predictor for both groups. It was significant for men ($\beta = 0.359$, $p < .001$) and even more so for women ($\beta = 0.573$, $p < .001$). This supports both H3a and H3b. These results imply that the easier and more intuitive the chatbot is to use, the more satisfied people are, especially women.

The results for identity-related gratification (which looks at personalization) were not significant in either group. For men, the estimate was very low ($\beta = 0.018$, $p = 0.120$) and for women it was even negative ($\beta = -0.135$, $p = 0.120$), with both not being significant. This means hypotheses H4a and H4b are both rejected. Personalization of the responses users receive does not seem to have a direct impact on user satisfaction.

Control and safety gratification had a small but significant effect for men ($\beta = 0.154$, $p = 0.043$), while it was not significant for women ($\beta = 0.036$, $p = 0.532$). This supports H5a but not H5b. This form of gratification, involving privacy and data security, appears to only influence men's satisfaction.

Finally, satisfaction strongly predicted loyalty for both groups. Men showed a stronger link ($\beta = 0.633$, $p < .001$), but it was also significant for women ($\beta = 0.364$, $p < .001$). That supports H6a and H6b. When people are satisfied with ChatGPT, they're more likely to keep using it and recommend it to others.

These results show that while some gratifications work similarly across groups, others seem to affect satisfaction differently for each gender. Trust gratification is more important for women, while control and safety stand out more for men.

5.3 Multigroup Analysis with Equality Constraints

To find out whether the differences between men and women we saw in the baseline model were actually significant, a multigroup analysis with equality constraints was conducted in AMOS. The first step involved estimating a structural weights model, in which all structural paths were constrained to be equal between male and female participants. This model was then compared to the unconstrained baseline model using a chi-square difference test. The result, $\Delta\chi^2(5) = 5.661$ with a p-value of .341, was not statistically significant. This suggests that setting all paths equal across the two groups did not significantly worsen model fit. In other words, the overall structure of the model appears consistent across gender, and the way the gratification types relate to satisfaction and loyalty does not fundamentally change between men and women.

To examine the potential for more specific gender differences, a series of five models was estimated.

In each of these, only one of the structural paths to satisfaction was constrained to be equal across the groups while all other paths stayed the same as in the baseline model. This way, each model tests for a specific relationship if there is a significant difference between men and women. These models were then compared with the unconstrained version using the same chi-square difference testing approach. The results of these comparisons are shown in Table 5.

Path Constrained	Δdf	$\Delta\chi^2$	p-value	Hypothesis	Supported
All structural paths (structural weights)	5	5.661	.341	–	–
Trust gratification → Satisfaction	1	1.297	.255	H4	No
Identity-related → Satisfaction	1	1.401	.237	H8	No
Instrumental → Satisfaction	1	0.096	.757	H2	No
Usability → Satisfaction	1	2.509	.113	H6	No
Control & Safety → Satisfaction	1	1.194	.275	H10	No

Table 5: Tests of structural path constraints ($\Delta\chi^2$ difference tests), with associated hypotheses and whether they were supported.

The table shows the results of chi-square difference tests for each gratification path constrained across gender groups. These tests show whether the relationship between each gratification type and satisfaction is significantly different for men and women.

Interestingly, although there seemed to be stark differences in some results in section 5.2 between the two groups, none of the individual paths showed a significant difference in their chi-square values. For example, the constraint on the path from trust to satisfaction had a p-value of .255, while in the baseline model, trust was significant for women but not for men. This result suggests that the difference in the trust path seen before is not large enough to be statistically meaningful. The same was true for all other gratification types. The highest chi-square difference was observed for the usability path, with a value of 2.509 and a p-value of .113. None of the p-values are below the conventional alpha level of .05 for significance.

The first row in the table refers to the structural weights model. In this model, all paths from the gratification types to satisfaction were constrained, making them equal across the two groups. The p-value for this test is .341. Since this value is also not significant, it indicates that applying equal constraints to all paths at once does not worsen model fit in a significant way.

While these findings and the results in 5.2 seems to be contradicting, it is not unusual in SEM. Constraint testing can show that observed differences in path strengths are actually not statistically significant. This can happen because differences in path strengths can look large when viewed separately, but when tested directly with constraints, do not lead to a significant drop in model fit.

Earlier research can offer clarity on this. Even when path coefficients differ between groups, these differences can often be explained by normal variation in the data [10]. Also, the chi-square test used is known to be quite sensitive. It can react strongly to small differences depending on sample size. Because of this, researchers have suggested that chi-square results be backed by other fit indices like CFI [41]. These indices are less affected by sample size and model complexity and help provide more balanced and clear results.

Together, these results support the conclusion that the structural relationships in the model do not differ significantly between male and female users. Although there are some numerical differences in the strength of the paths, those differences are not large enough to be statistically meaningful. Therefore, the overall structure of gratification leading to satisfaction can be considered similar across gender groups.

6 Discussion and Implications

6.1 The Role of the Gratification Types

Uses and Gratifications theory has been widely used to explain the behavior of media users by focusing on the needs they aim to fulfill through different platforms. This study applied that same framework to ChatGPT. The results show both consistent patterns and small gender-based differences in how people experience satisfaction. Instrumental gratification and usability gratification had a strong effect on satisfaction for both men and women. These findings support several core ideas of U&G theory. One of them is that users are active participants who engage with technology to meet specific personal needs. The significant impact of these types of gratification for both genders confirms that efficiency and ease of use remain central motivations for interacting with generative AI chatbots like ChatGPT, which is in line with earlier research [49].

Trust gratification only influenced satisfaction for women. This aligns with earlier work showing that women place more importance on reliability when using technology [35]. It can also be a reflection of a bigger digital pattern where women are more cautious with new technology. For men, trust did not have a significant effect. This could mean that they value accuracy less, and could even be linked to the idea that men are more confident using technology [59]. That confidence could make them less sensitive to being discouraged by weaker responses. This gender-based difference found in trust gratification partially supports existing literature on digital trust and confidence. Prior studies have shown that women are more cautious with new technologies and more sensitive to the credibility of information. Trust appeared to play a more important role for women, even though this difference was not statistically significant in the multigroup analysis. This still supports the idea that gender can influence which types of gratification matter most for satisfaction, even if the effect is not as strong as hypothesized.

In contrast, control and safety gratification was only significant in predicting satisfaction for men. This is an unexpected result, as earlier research has pointed out that women often have higher privacy concerns [54]. The survey questions on control and safety (Appendix B) measure the importance of technical reassurance. For men, this reassurance could act as proof that they are in charge of the interactions and of the way their data is handled. For women, this sense of control might not be important enough to influence their satisfaction with ChatGPT. Compared with trust gratification, it seems that men look more for control, while women look for signs of accuracy of the content.

This result complicates earlier findings in U&G theory. Several studies have reported that women

are more concerned about privacy and personal data in online environments [33]. However, the analysis showed that control and safety gratification only predicted satisfaction for men. They seemingly place more value in technical forms of control, such as understanding how their data is handled or being confident in how the system behaves. For women, similar needs might already be addressed through trust gratification. Since the survey items focused on technical reassurance, this could explain why control was more strongly linked to satisfaction for male users.

Identity-related gratification did not predict satisfaction for either group. This finding contradicts previous research on the influence of personalization and recognition on user engagement in digital media [11]. Identity-related gratification has shown to allow users to express themselves and feel seen.

One explanation for the results could be that users do not look for a strong personal bond with ChatGPT. The features in the questions on personalization might not be the priority when a user wants to get answers or complete a task. They could go unnoticed by users or not be valued enough to have a significant impact. This result points to a possible broader limitation in how identity gratification applies to AI interactions. While ChatGPT can mimic personalization through prompt responses, this does not show any effect on satisfaction in this case. This challenges the current importance of identity-related gratification the in U&G framework.

6.2 Comparing the Baseline and Multigroup Models

While the baseline model invites the idea of gender differences in the effects of certain kinds of gratification on user satisfaction, the constrained models bring those findings into perspective. When every path from the five gratifications to satisfaction was constrained for the two groups, the model did not worsen significantly ($\Delta\chi^2 = 5.661$, $p = .341$). Evidently, neither did constraining each of the paths separately. This leads to the conclusion that gender did not play a significant role in the strength of these relationships. These results suggest that the previously observed gender-based differences are not strong enough to conclude that satisfaction is built differently for men and women. The core structure of how each type of gratification predicts satisfaction is similar for both groups. While the sample is large, a more diverse sample might be needed for the expected gender differences to become clear, as the current sample consists of only highly educated corporate employees. It is possible that other factors, such as age or education, play a bigger role than gender [12, 27].

These results raise questions about how demographic variables shape user satisfaction beyond gender. While gender has consistently been a main focus in U&G research, it did not lead to any major differences in this study. One partial explanation for this could be that people mainly use generative AI chatbots to complete tasks efficiently, rather than to express themselves or for personal connection, which are where the biggest gender differences lie. The sample could also play a role, as most participants came from similar professional backgrounds, which could have made gender less relevant.

6.3 Alternative Survey Design

Because the framework of this research was built around the already existing dataset, it was predetermined what kinds of gratifications could be tested based on the survey dimensions. If the survey had instead been created to align with U&G theory from the start, there could have been improvements made.

A few of the types of gratification formulated in this study are considerably niche in U&G theory. There are certain types that are more widely known and explored, and might have been more beneficial to research. A few of the most popular gratifications in U&G research are information seeking, entertainment, social connection and escapism [52]. Out of these, information seeking is the only one that this study explicitly researched. A survey that also centered on the rest of them could gain results that are easier to compare and back with earlier studies. For example, entertainment could be measured by asking users if they sometimes use ChatGPT out of curiosity without a particular goal or purpose, or if they find enjoyment in interacting with ChatGPT. Such questions are directly connected to motives that are strongly recognized in literature and therefore strengthen the theoretical fit of the model.

Some of the gratification types currently in the study could also have been explored further with different survey questions. In the case of identity-related gratification, questions could focus more on whether users feel recognized by the system and can express themselves clearly. Making certain questions broader could create a more complete picture of people's experience with ChatGPT and the gratifications they look for.

6.4 Theoretical Implications

The findings of this study support several of the core ideas of Uses and Gratifications theory. Users engage with generative AI chatbots to meet specific needs, and their satisfaction depends on how well those needs are met. Instrumental and usability gratification were clearly the most influential, which shows that efficiency and ease of use remain central needs when dealing with GenAI systems. This confirms that classical gratifications from earlier U&G research still apply.

At the same time, the study shows the limits of the more niche gratifications without strong theoretical grounding. Identity and control gratification are less developed in earlier literature than the other types of gratification, which is reflected in the results. These gratifications had weak effects on satisfaction for at least one of the groups and were inconsistent, suggesting that the way these constructs were measured might not fully capture how users actually experience them.

In a broader context, the results of the study question if and how U&G theory can be made to fit evolving technology like generative AI chatbots. While the theory still offers a useful framework for gaining insights into user motivations, some gratification types might need to be adjusted. Constructs like identity and control may not function in the same way as they do in traditional or social media. Generative AI chatbots like ChatGPT are often used for quick, goal-oriented tasks, which does not leave much space for expressing identity or forming a sense of personal control over

the interaction, at least in its current form.

This shift in how people engage with technology may also help explain why gender differences were not as strong as expected. While the baseline results showed some variation in which gratifications mattered more for men or women, the constrained models showed that these differences were not significant. Future research may benefit from exploring other user characteristics beyond gender, such as other demographic features, digital skills, or user confidence.

6.5 Practical Implications

The study presents insights that could be useful for developers of chatbots. Instrumental and usability gratification have a strong effect on user satisfaction, and these should remain priorities. Most users approach AI chatbots with a clear goal in mind. They want the tool to help them complete tasks quickly and without difficulty. A smooth and easy-to-use interface is of the utmost importance. Clear responses and only requiring low effort input to complete tasks are also important for the user experience. These practical needs should remain at the core of design decisions, especially as generative AI chatbots become more embedded in everyday workflows.

The findings also point to a gap between the features available and what users actually notice. While personalization, transparency and control were part of the survey, their impact on satisfaction was more limited compared to efficiency and usability. If the system offers features that can fulfill certain needs but does not show them clearly, they could go unnoticed to users. Developers could experiment with settings to match user preferences in these areas. One example would be to offer a clear option to change the tone of the responses. Making options like these directly available in the interface makes them more noticeable. Furthermore, allowing users to easily access and adjust how their data is stored or how their conversations are used could increase their sense of control and trust. Such settings can help build a more flexible and inclusive system that adapts to different expectations and improve user experience.

It is also important to recognize that different users have different goals and expectations when interacting with AI. Designing the system to respond to these different goals could make it feel more personal and useful. These improvements can be made with small adjustments and lead to more needs being met. Making existing features more accessible and linking them more clearly to what users actually want will be the key in matching users' needs as generative AI chatbots evolve.

6.6 Limitations and Future Research Directions

The biggest limitation in this study is the use of a secondary dataset. This meant that the survey questions and dimensions were already defined. While the questions worked well for the five gratification types described in the study, there were gaps in emotional and social needs which were not explored. These missing elements might have given a more complete view of how users experience ChatGPT.

The sample itself formed another limitation. While the survey had a relatively large number of participants, they all had fairly similar backgrounds. All of them were highly educated and had similar work environments. This limits the generalisability of the results, as the gratification types could have different impacts for men and women depending on ages or backgrounds. Additionally, as the participants were all corporate employees, people who use ChatGPT for more creative purposes or other motivations might be underrepresented.

To cover these limitations, future research should aim to collect a diverse sample on a survey that is designed in alignment with the U&G theory. Users with different demographic characteristics, as well as different levels of digital skills and motivations for using GenAI, might give more complete insights into the role of gratifications on user satisfaction. Combined with a survey that intentionally measures relevant types of gratification, this method could help understand how users engage with generative AI chatbots. This would strengthen the theoretical foundation for future studies and provide a more accurate picture of how AI tools meet the diverse needs of their users.

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7 Appendix

A Demographic Survey Items

- **Gender:**
  - Male
  - Female
- **Age:**
  - Between 18 and 20 years
  - Between 21 and 25 years
  - Between 26 and 35 years
  - Between 36 and 45 years
  - Between 46 and 55 years
  - Over 55 years
- **Education:**
  - Currently enrolled in studies
  - Basic or professional studies
  - University studies
  - Master's or PhD studies
- **Frequency of ChatGPT use:**
  - Intensively every day
  - Once per day
  - Once per week
  - In very few occasions

B Survey Dimensions

- **Efficiency (EFF1–EFF5)**
  - EFF1 ChatGPT helps me complete tasks quickly.
  - EFF2 ChatGPT increases my productivity.
  - EFF3 ChatGPT saves me time.

  - EFF4 ChatGPT is useful for practical tasks.
  - EFF5 ChatGPT helps me achieve my goals efficiently.

- **Trust (ASS1–ASS4)**
  - ASS1 I trust the information provided by ChatGPT.
  - ASS2 ChatGPT provides consistent answers.
  - ASS3 ChatGPT gives accurate responses.
  - ASS4 I rely on ChatGPT for trustworthy information.

- **Interface and Presentation (I&P1–I&P3)**
  - I&P1 ChatGPT is easy to use.
  - I&P2 The interface of ChatGPT is clear and intuitive.
  - I&P3 ChatGPT is visually appealing.

- **Personalization (PER1–PER3)**
  - PER1 ChatGPT tailors responses to my preferences.
  - PER2 ChatGPT feels like it understands my personal context.
  - PER3 I feel that ChatGPT adapts to me over time.

- **Privacy and Security (P&S1–P&S4)**
  - P&S1 I feel that my data is safe when using ChatGPT.
  - P&S2 ChatGPT respects my privacy.
  - P&S3 I am aware of how my information is used.
  - P&S4 I feel in control of what I share with ChatGPT.

- **Satisfaction (SAT)**
  - SAT Overall, I am satisfied with my experience using ChatGPT.

- **Loyalty (LOY1–LOY3)**
  - LOY1 I intend to keep using ChatGPT in the future.
  - LOY2 I would recommend ChatGPT to others.
  - LOY3 I prefer ChatGPT over other AI tools.