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Research Article

Understanding the Different Generational Motivations and Adoption of AI in Families: Integrating Technology Acceptance and Uses and Gratifications Theory

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ARTICLE INFO	ABSTRACT
Received: 30 Dec 2024 Revised: 14 Feb 2025 Accepted: 24 Feb 2025	This study examines AI adoption within families through a generational lens, revealing how age-related motivations shape AI engagement across generations. By integrating the Technology Acceptance Model (TAM) and Uses and Gratifications (U&G) theory, this research explores extrinsic and intrinsic drivers of AI use, uncovering how factors influence AI adoption among adolescents and parents. Surveying 120 families, including 200 adolescents and 160 parents, we employed SEM-PLS to validate our model, revealing distinct patterns in AI preferences across age groups. Findings indicate that while ease of use, usefulness, and socialization consistently drive AI engagement, personal integrative factors are especially impactful within the Iranian context. Our results highlight intergenerational differences that inform family-centered AI design and policy, offering a culturally nuanced framework for AI development that bridges generational divides. This study delivers insights for policymakers, and researchers, providing a roadmap for inclusive AI adoption strategies that honor cultural and generational needs within families. **Keywords:** AI Use, Family, Technology Acceptance Model (TAM), Uses and Gratification Theory (U&G), and Generational Differences

INTRODUCTION

The explosion of artificial intelligence (AI) in everyday life is reshaping family dynamics in profound ways (Kislev, 2022). From voice-activated assistants to smart home ecosystems, AI is transforming how generations interact, make decisions, and manage household tasks (Dwivedi et al., 2021; Noorbehbahani et al., 2024). With 60% of households in tech-forward regions now using at least one AI-enabled device, AI is embedding itself in domestic routines—supporting convenience, personalization, and connection (Statista, 2023). Voice assistants have become pivotal family tools, coordinating schedules, managing smart devices, and offering seamless access to an array of digital resources. Yet, while AI's footprint in the home grows, stark generational differences in usage and perception emerge, highlighting an urgent need to understand how these technologies are shaping family life across age groups.

Youth, in particular, are captivated by AI-driven educational and social applications, while parents often remain in the dark about their children's engagement with AI (Druga, 2023). This disconnects between generations raises concerns among health and family advocates regarding privacy, safety, and informed AI usage. As AI's capabilities expand, so do the potential benefits and risks, making it critical to understand how family members across

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generations adopt, engage with, and perceive these technologies.

While prior research on AI adoption focuses predominantly on workplace productivity and institutional learning (Bag et al., 2021; Wang et al., 2021), motivations within family settings reflect unique, underexplored dynamics. Family-oriented AI use is often driven by intrinsic motivators such as enjoyment, novelty, and social bonding, revealing an entirely different adoption landscape compared to professional settings. The Technology Acceptance Model (TAM)(Davis, 1989; Davis et al., 1989), which emphasizes ease of use and perceived usefulness, may not capture the full spectrum of motivations present in domestic AI use, where factors like self-expression, enjoyment, and socialization become equally, if not more, significant. Understanding these nuanced generational motivations for AI engagement is crucial for shaping the future of AI in family life.

This study explores the intersection of generational perspectives and motivations in family AI adoption, focusing on factors such as ease of use, perceived usefulness, socialization, self-presentation, enjoyment, novelty, and unique functionality. This exploration arrives at a pivotal time, as AI continues to permeate family life, necessitating a framework that captures how functional and experiential motivations intersect in family settings. Findings from this research offer key insights for developing age-appropriate, family-centered AI applications that bridge generational divides and foster enhanced family interactions.

To conceptualize these motivations, this study integrates two powerful frameworks: the TAM and Uses and Gratifications (U&G) theory (Katz et al., 1973). TAM has been a cornerstone in predicting technology adoption, emphasizing extrinsic motivations like ease of use and usefulness. However, these workplace-centered drivers miss intrinsic motivations central to family interactions, where technology often fulfills social and personal gratifications. By merging TAM with U&G, which addresses how people seek personal and social gratifications, this study aims to provide a multi-dimensional understanding of AI adoption in families, capturing both functional and experiential factors that influence generational perspectives on AI.

In sum, this study presents a novel model that explains how generational differences shape family AI adoption, addressing both extrinsic and intrinsic motivations. This framework contributes essential insights for educators, policymakers, and designers of family-oriented AI, offering strategies for fostering responsible, balanced AI engagement. By understanding each generation's unique motivators, this research paves the way for AI applications that enhance family cohesion and provide meaningful, positive impacts in households across generations.

THEORETICAL FRAMEWORK

Technology Acceptance Model (TAM)

TAM has long been a foundational framework for understanding technology adoption, focusing originally on workplace settings (Na et al., 2022). TAM highlights two primary constructs: perceived ease of use (PEoU) and perceived usefulness (PU) (Davis, 1989). PEoU is defined as the degree to which an individual believes a technology will be free of effort, while PU reflects the belief that the technology will enhance performance or fulfill specific needs (Venkatesh & Davis, 2000). Although initially task-oriented, TAM's adaptability across diverse settings—including family environments—enables it to capture motivations for adopting AI-driven technologies that differ from professional contexts.

In family settings, AI often serves dual roles: it not only provides functional support but also enhances social connections, manages daily routines, and enriches shared experiences (Nagy, 2018; Tefertiller, 2020). Within families, PEoU takes on unique significance as generational differences in technological familiarity impact perceptions of ease of use. For example, younger family members, often more technologically adept, tend to engage more readily with AI than older relatives, fostering a dynamic of intergenerational support where younger members guide and encourage others (Reis et al., 2021). PU in family settings also takes on new dimensions, extending beyond efficiency to relational benefits, such as enhancing family bonding and supporting collective activities (Hertlein & Blumer, 2013). Studies indicate that when AI aligns with family goals—like promoting convenience, ensuring safety, or facilitating social connection—adoption is more likely (Cha, 2013; Venkatesh & Bala, 2008). By exploring PEoU and PU through a family-centered lens, TAM provides nuanced insights into AI adoption within households, revealing how intergenerational dynamics and shared family needs shape adoption motives.

Uses and Gratification Theory

U&G explores how people actively seek out technologies based on specific personal and social needs (Florenthal, 2019). In family AI use, U&G suggests that members interact with AI not just for functionality but to fulfill intrinsic gratifications such as social connection, enjoyment, novelty, and self-expression (Hwang et al., 2024). Younger family members may engage with AI-enabled tools for entertainment, satisfying curiosity, or social interaction, meeting U&G needs for novelty and social bonding (Shao & Kwon, 2019). Conversely, older family members may value AI's practical benefits for managing household tasks (Czaja & Ceruso, 2022), while appreciating how it promotes a sense of inclusion in the family's technology use. This multi-faceted engagement aligns with U&G's perspective that media use is driven by diverse motivations (Dhir et al., 2017).

U&G theory further proposes that users adapt technology to satisfy evolving gratifications, which, in the context of AI, includes experiential and relational benefits. For example, AI use for collaborative activities—such as planning family events or engaging in virtual game nights—satisfies intrinsic motivations for connection, fostering relational closeness across generations (Nagy, 2018). These experiences support AI's role as a facilitator of family cohesion, aligning with U&G's view that technology use is deeply intertwined with interpersonal needs (Dhir et al., 2016). U&G thus underscores the importance of family routines and shared experiences, illustrating how perceived gratifications can reinforce AI's relevance and strengthen familial bonds in an increasingly digital world.

The Research Model and Hypotheses

The integration of TAM and U&G in this research model provides a comprehensive view of the motivations behind AI adoption in family contexts. This model suggests that both extrinsic motivations (PEoU and PU) and intrinsic motivations (socialization, enjoyment, novelty, unique functionality, and self-presentation) drive generational engagement with AI. By extending TAM with U&G, this framework combines functional and experiential dimensions of AI use, offering insights into how these factors collectively influence family members' adoption intentions (See Figure 1 for the research model).

In line with TAM, PEoU is proposed as a key precursor to PU, indicating that technologies perceived as user-friendly will be seen as more beneficial in family interactions (Davis, 1989). Research highlights that digital proficiency often affects these perceptions, with younger family members finding technology more accessible, resulting in higher PU perceptions compared to older members (Zhou et al., 2014). Within this model, PU goes beyond productivity, encompassing family-centered benefits such as improved communication, coordination, and safety, which resonate differently across age groups (Barbul & Bojescu, 2023). For example, AI's role in managing schedules or enhancing security directly impacts family members' quality of life (Dwivedi et al., 2021). To broaden TAM's utility, U&G's social utility construct addresses motivations for socialization and self-presentation, particularly relevant in family settings where members seek connection. AI thereby supports family cohesion through shared activities, aligning with younger users' desire for self-expression and social engagement.

Enjoyment and novelty—key drivers of hedonic utility—are also crucial motivators in AI engagement (Y. W. Kim et al., 2024). U&G theory posits that technology adoption often stems not only from practical needs but from experiential rewards like entertainment and curiosity (Lin & Bhattacherjee, 2010). Enjoyment fosters sustained technology use, as younger users find interactive AI engaging, while older members may appreciate the novelty AI brings to daily tasks (Kim et al., 2013). Recognizing these hedonic aspects provides a more nuanced view of AI's appeal across generations. Moreover, the functional utility, or AI's practical benefits, reinforces PU by addressing specific family needs through automation, resource management, and voice commands (Maksimainen & Saariluoma, 2010). This blending of functionality with enjoyment positions AI as a relevant tool for meeting diverse generational expectations and enhancing family efficiency.

The model also incorporates generational influence as a moderating factor, affecting the relationships between PEoU, PU, and AI adoption intentions. Intergenerational dynamics foster a collaborative environment where younger, more tech-savvy members may encourage older members to use AI, thus enhancing perceived ease of use and usefulness across the family (Selwyn, 2004). Evidence suggests that family support can facilitate technology adoption, fostering a cooperative approach to exploring AI's potential (Chen & Chan, 2014). Hence, generational influence emphasizes the family's role in shaping individual attitudes toward AI. Based on the proposed model, the study posits the following hypotheses:

1. PEoU positively impacts PU in family settings.

2. PEoU directly affects motivations, including (a) socialization, (b) self-presentation, (c) enjoyment, (d) novelty, and (e) unique functionality of AI.

3. PU directly affects motivations, including (a) socialization, (b) self-presentation, (c) enjoyment, (d) novelty, and (e) unique functionality of AI.

4. Motivations such as (a) socialization, (b) self-presentation, (c) enjoyment, (d) novelty, and (e) unique functionality significantly influence AI adoption intentions.

5. PU has a positive impact on AI adoption intentions.

6. PEoU positively influences AI adoption intentions.

7. Generational differences moderate relationships between predictors and AI adoption intentions.

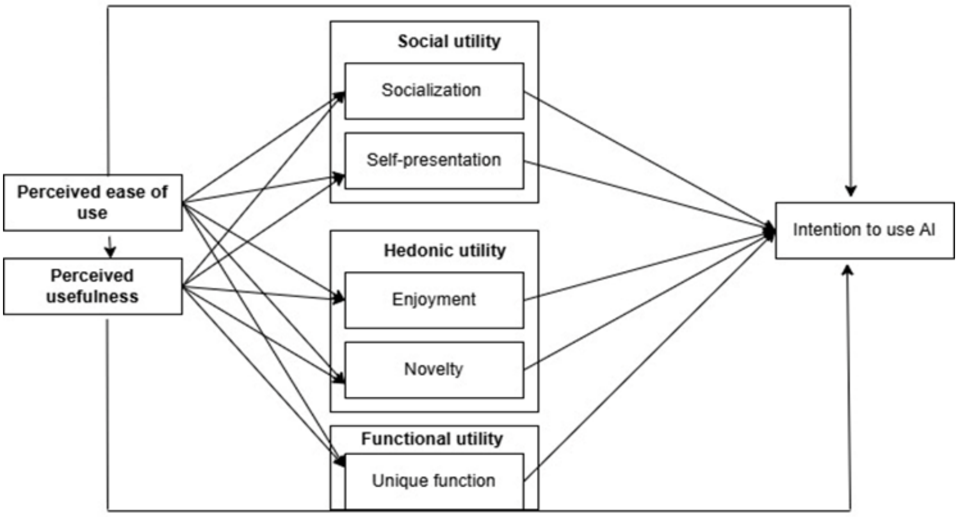

Figure 1: Research Model.

RESEARCH METHODOLOGY

Participants and Procedures

This study adopts a cross-sectional, correlational design and includes a sample of 120 families with adolescents aged 10 to 17 from Tehran, Iran. To ensure diverse socioeconomic representation, a stratified random sampling method was used. Participants were recruited from six schools, each representing distinct socioeconomic strata, providing a robust basis for analyzing family technology use across varying contexts. Collaboration with school principals and administrative staff facilitated effective recruitment, enhancing student and family participation.

To encourage engagement and reliable responses, the study prioritized transparency (Lupia & Alter, 2014). Parents received comprehensive information on the study's goals, data collection methods, and data confidentiality assurances. Informational sessions at each school allowed facilitators to address questions from both parents and students, reinforcing anonymity and data protection measures. Data collection commenced in 2024, following informed consent from both parents and adolescents. To minimize potential biases associated with collective family responses, interviews were conducted individually with each family member. Special attention was given to creating a comfortable interview environment, encouraging open and honest expression.

In total, 160 valid responses were collected from adolescents, and 200 from parents. This discrepancy, attributed to parental participation encouragement, provided a rich dataset for a comprehensive examination of family technology interaction patterns.

Measurement

The study's research instrument consists of two sections: the first for demographic data and the second for measuring constructs in the proposed research model. The second section employs a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) to assess responses. Construct measures were adapted from established literature: intention, perceived ease of use, and perceived usefulness items from Choung et al. (2023); novelty items from Jishnu et al. (2023); socialization and self-presentation items from Lee et al. (2016); and perceived enjoyment and unique functionality items from Marjerison, et al. (2022). Table 1 provides further detail on the measurement items.

To assess the instrument's reliability and validity, we conducted tests for outer loadings, Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) for each construct. Items with outer loadings above 0.70 were retained, while items with lower loadings were removed to strengthen reliability. Cronbach's alpha values (0.700–0.887) indicated satisfactory internal consistency, and CR values exceeded the recommended 0.70 threshold, confirming reliability. AVE values also met the 0.50 benchmark, verifying convergent validity. These metrics affirm the instrument's robustness and suitability for assessing the constructs within the model.

Table 1: The Measuring Items.

	Items	Outer loading	α	CR	AVE
	INT	0.913	0.887	0.889	0.815
1	I intend to continue using AI.	0.911			
2	I predict that I will continue using AI.	0.884			
3	Using AI is something I would continue to do.	-			
	PEoU		0.710	0.700	0.758
1	Learning to use AI would be easy for me.	-			
2	I would find it easy to get AI to do what I want it to do.	0.881			
3	My interaction with AI is clear and understandable.	0.861			
4	It would be easy for me to become skillful at using AI.	-			
5	I would find AI to be easy to use.	-			
	PU		0.700	0.701	0.768
1	Using AI would enable me to accomplish tasks more quickly.	-			
2	Using AI would improve my performance at accomplishing tasks.	-			
3	Using AI for accomplishing tasks would increase my productivity.	-			
4	Using AI would enhance my effectiveness at accomplishing tasks.	0.874			
5	I find AI useful for me to accomplish tasks.	0.879			
	SOC		0.784	0.786	0.699
1	I use AI tools to stay connected with my family.	-			
2	AI helps us keep updated on each other's activities within the family.	-			
3	AI makes it easier to interact with family members, even if we are apart.	0.849			
4	AI enables me to strengthen my relationships with family members.	0.780			
5	I use AI to share experiences and memories with my family.	0.877			
	SEP		0.809	0.821	0.722
1	I use AI tools to share my interests and hobbies with my family.	-			
2	AI helps me present my ideas and perspectives to family members.	-			
3	I use AI to communicate my achievements with my family.	0.818			
4	Through AI, I can express my personality when interacting with family.	0.868			

5	AI allows me to share personal updates with my family in a unique way.	0.863			
	ENJ		0.887	0.898	0.699
1	I enjoy using AI for activities that involve my family.	0.849			
2	Using AI with my family is a fun experience.	-			
3	I find it enjoyable to use AI for shared family activities.	0.898			
4	AI adds enjoyment to my interactions with family members.	0.903			
5	Engaging with AI as a family brings me joy.	0.863			
	NOV		0.838	0.851	0.753
1	I use AI because it is new	0.841			
2	I use AI because it is innovative	0.894			
3	I use AI as it is unusual.	0.867			
	UNF				
1	AI offers unique ways for my family to connect and communicate.	-	0.870	0.903	0.673
2	I rely on AI to make certain interactions with my family easier.	0.866			
3	AI provides special tools that improve family communication.	0.911			
4	I use AI to do things with my family that we couldn't do otherwise.	0.867			
5	AI allows us to have unique experiences as a family.	0.881			

Note. Intention to use = INT, Perceived ease of use = PEoU, Perceived usefulness = PU, Socialization = SOC, Self-presentation = SEP, Enjoyment = ENJ, Novelty = NOV, Unique function = UNF.

Data analysis

The research model (Figure 1) was analyzed using structural equation modeling (SEM) with partial least squares SEM (PLS-SEM), an approach ideal for complex and exploratory models. Following Hair and Alameret (2022), a two-step approach was applied, evaluating both the measurement and structural models. First, the measurement model was examined to ensure reliability and validity, followed by an analysis of the hypothesized relationships within the structural model. Additionally, PLS-multiple group analysis (PLS-MGA) was conducted to investigate potential differences in model relationships between adolescents and their parents. All data analyses were performed using SmartPLS 4.1.0.9.

RESULTS

Sample Characteristics

Table 2 summarizes the demographic characteristics of the adolescents (n = 200) and parents (n = 160) included in the study. The adolescent group had a mean age of 16.8 years (SD = 1.68), while the parent group had a mean age of 42.5 years. The gender distribution was relatively balanced in both groups, with 52% of adolescents and 55% of parents identifying as women. Regarding education, 10% of adolescents had completed elementary education, 75% had secondary education, and 15% held a university degree, with no adolescents reporting a postgraduate degree. Among parents, 9.4% had completed elementary education, 25% had secondary education, 43.8% had a university degree, and 21.8% held a postgraduate degree. Marital status data indicated that 81.3% of parents were married or cohabiting, 9.4% were unmarried, 6.3% were divorced, and 3.1% were widowed. Socioeconomic status (SES) distributions for adolescents revealed that 10% were classified as high or upper-middle class, 50% as middle class, 30% as lower-middle class, and 10% as low SES. For parents, 31.3% were in the high or upper-middle class, 43.8% in the middle class, 18.8% in the lower-middle class, and 6.3% in the low SES group.

Table 2: Descriptive statistics (n and % mean).

Demographic variables	Adolescents			Parents	
	n	(mean) %	SD	n	(mean) %
Age (mean)	200	16.8	1.68	160	42.5

Gender (%)					
Women	104	52%	-	88	55%
Men	96	48%	-	72	45%
Educational level					
Elementary	20	10%	-	15	9.4%
Secondary	150	75%	-	40	25%
University degree	30	15%	-	70	43.8%
Postgraduate	-	-	-	35	21.8%
Marital status (%)					
Married/Cohabiting	-	-	-	145	81.3%
Unmarried	-	-	-	-	9.4%
Divorced	-	-	-	10	6.3%
Widowed	-	-	-	5	3.1%
Socioeconomic Status					
High and Upper-Middle	20	10%	-	50	31.3%
Middle	100	50%	-	70	43.8%
Lower-Middle	60	30%	-	30	18.8%
Low	20	10%	-	10	6.3%

Generational Differences in AI Use

Table 3 presents generational differences in the use of various AI technologies. Several significant differences were observed in the usage of AI devices between adolescents and parents. Adolescents reported significantly higher usage of smart TVs ($M = 1.74$, $SD = 2.39$) compared to parents ($M = 1.45$, $SD = 1.21$), with a significant difference ($p = .003$). Similarly, adolescents used gaming consoles with AI assistants more frequently ($M = 5.42$, $SD = 1.54$) than parents ($M = 5.06$, $SD = 2.03$), with a significant difference ($p = .040$).

Adolescents also reported higher usage of smart home gadgets, such as thermostats ($M = 3.57$, $SD = 2.63$), compared to parents ($M = 2.67$, $SD = 2.05$), with a significant difference ($p = .002$). AI personal assistants (e.g., Alexa) were used significantly more by adolescents ($M = 3.20$, $SD = 2.39$) than by parents ($M = 2.41$, $SD = 2.06$), with a very strong difference ($p < .001$). Similarly, adolescents reported higher usage of AI chatbots on social media ($M = 2.43$, $SD = 2.47$) compared to parents ($M = 2.09$, $SD = 1.75$), with a significant difference ($p = .001$). However, no significant generational differences were found for the use of smartphones with AI apps ($p = .071$), smart speakers ($p = .087$), or wearable AI devices ($p = .071$).

Table 3: Generational Differences in AI Use.

Type	Parents		Adolescents		
	M	SD	M	SD	P
Smartphones with AI Apps (e.g., Gemini, etc.)	3.29	2.17	3.69	2.03	.071
Smart Speakers (e.g., Amazon Echo, etc.)	2.39	1.98	3.05	2.45	.087
Smart TVs (e.g., Samsung, LG, etc.)	1.45	1.21	1.74	2.39	.003
Gaming Consoles with AI Assistants (e.g., x-box, etc.)	5.06	2.03	5.42	1.54	.040
Wearable AI Devices (e.g., Smartwatches)	3.57	2.37	4.36	2.00	.071
Smart Home Gadgets (e.g., Thermostats)	2.67	2.05	3.57	2.63	.002
AI Personal Assistants (e.g., Alexa, etc.)	2.41	2.06	3.20	2.39	<.001
AI Chatbots in social media	2.09	1.75	2.43	2.47	.001

Measurement Model Analysis

Discriminant validity of the measurement model was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio, as shown in Table 4. The Fornell-Larcker criterion confirmed discriminant validity, as the square roots of the AVE for each construct were higher than its correlations with other constructs. Additionally, the HTMT values, all below 0.85, further supported the discriminant validity of the constructs, with the highest value being 0.840 for the correlation between "Self-Presentation" and "Novelty."

Table 4: Discriminant Validity (Fornell-Larcker criterion and HTMT).

No.	Constructs	1	2	3	4	5	6	7	8
1	INT	0.871	0.868	0.818	0.831	0.868	0.868	0.868	0.768
2	PEoU	0.819	0.817	0.811	0.811	0.871	0.871	0.871	0.821
3	PU	0.769	0.697	0.820	0.643	0.512	0.53	0.639	0.816
4	SOC	0.751	0.756	0.610	0.833	0.729	0.631	0.61	0.606
5	SEP	0.823	0.651	0.676	0.822	0.898	0.85	0.72	0.679
6	ENJ	0.768	0.782	0.733	0.771	0.813	0.877	0.679	0.665
7	NOV	0.878	0.756	0.732	0.827	0.840	0.859	0.883	0.665
8	UNF	0.803	0.761	0.661	0.709	0.737	0.799	0.799	0.838

Note. Intention to use AI= INT, Perceived ease of use = PEoU, Perceived usefulness = PU, Socialization = SOC, Self-presentation = SEP, Enjoyment = ENJ, Novelty = NOV, Unique function = UNF, Bold values are the square root of AVE; values below the diagonal denote inter-correlation between constructs; Italic values mean HTMT values.

Structural Model Analysis

The structural model analysis investigated the relationships between PEoU, PU, motivations, and AI adoption intentions among adolescents and parents. The R-squared (R^2) values for the model's constructs indicated varying explanatory power. The R^2 value for AI adoption intention was the highest at 0.661, meaning 66.1% of the variance in adoption intention was explained by the predictors. Enjoyment (R^2 = 0.466) and novelty (R^2 = 0.312) showed moderate to low explanatory power. The R^2 values for perceived usefulness (0.427), self-presentation (0.458), and unique functionality (0.398) were moderate, while socialization had the highest explanatory power with an R^2 of 0.531. The adjusted R^2 values were consistent, confirming the robustness of the model.

The model fit was good, as evidenced by the SRMR value of 0.041 and NFI of 0.956. The Q^2 values ranged from moderate (intention to use AI = 0.494) to weak (novelty = 0.222), highlighting that while the model explained some variance and showed strong fit for certain variables, predictive relevance was variable.

Hypothesis Testing

The first hypothesis proposed that PEoU directly influences PU. This hypothesis was supported by the results. The total sample path coefficient was 0.641 (t = 18.371), indicating a significant relationship. When separated by groups, the path coefficients were 0.489 (adolescents, t = 16.690) and 0.532 (parents, t = 17.540), demonstrating that PEoU positively influences PU in both groups, with minor differences between adolescents and parents. The second hypothesis suggested that PEoU directly influences motivations such as socialization, self-presentation, enjoyment, novelty, and unique functionality of AI. This hypothesis was supported, though the strength of the relationships varied. For example, PEoU had a stronger effect on socialization for adolescents (0.367, t = 9.653) compared to parents (0.310, t = 7.50). The strongest effect was observed for novelty, particularly among adolescents (0.543, t = 18.15), indicating a heightened sensitivity to ease of use when exploring new AI features.

In addition, the third hypothesis, proposing that PU directly influences motivations, was supported. PU significantly influenced all five motivations, with the strongest effects observed for enjoyment (0.577, t = 17.75) and self-presentation (0.425, t = 6.179) for both groups. However, PU did not significantly influence socialization ($p > 0.05$), suggesting that while PU drives several motivations, its influence on socialization is weaker. The fourth hypothesis posited that motivations, such as socialization, self-presentation, enjoyment, novelty, and unique functionality, significantly influence AI adoption intentions. This hypothesis was partially supported. Enjoyment (0.314, t-value = 3.591), novelty (0.168, t = 2.396), and unique functionality (0.233, t-value = 3.22) positively influenced AI adoption intentions. However, socialization (0.067, t = 0.844) and self-presentation (0.059, t = 0.669) did not significantly affect adoption intentions, suggesting that some motivations, such as socialization and self-presentation, are weaker predictors of adoption.

The fifth hypothesis, which suggested that PU has a positive effect on AI adoption intentions, was fully supported. PU significantly impacted AI adoption intentions with a path coefficient of 0.521 (t = 8.199), confirming that the perceived usefulness of AI plays a key role in driving adoption intentions for both adolescents and parents. This finding supports the hypothesis that the more useful individuals perceive AI to be, the more likely they are to adopt it. The sixth hypothesis, proposing that PEoU has a positive effect on AI adoption intentions, was also supported. PEoU positively influenced AI adoption intentions with a path coefficient of 0.203 (t = 3.419) for the total sample. The path coefficients were higher for adolescents (0.223, t = 5.876) compared to parents (0.149, t = 3.795), indicating that adolescents are more likely to adopt AI when it is perceived as easy to use. This result supports the hypothesis, showing that PEoU plays a stronger role in shaping adoption intentions for adolescents than for parents.

The seventh hypothesis, which suggested that generational differences moderate the relationships between predictors and AI adoption intentions, was also supported. Moderating effects were observed in several relationships, particularly between motivations and adoption intentions. For instance, the difference in path coefficients for PEoU's impact on novelty was 0.061 (t = 1.005), with adolescents showing a stronger effect (0.543, t = 18.15) compared to parents (0.507, t = 12.826). Additional moderating effects were found in the relationships between motivations and adoption intentions, particularly for enjoyment and novelty, highlighting the significant role of generational context in shaping AI adoption behaviours. This finding supports the hypothesis that generational differences moderate the relationships between predictors and AI adoption intentions.

Table 5: Results of the Structural Model between Adolescents and their Parents.

Paths	Path coefficient (t-value) Total (n=360)	Adolescent (n=200)	Parents (n=160)	Δ Path coefficients	t
PEoU → PU	0.641(18.371***)	0.489(16.690***)	0.532 (17.54***)	0.053	1.030
PEoU→SOC	0.273 (4.253***)	0.367 (9.653***)	0.310 (7.50***)	- 0.036	0.733
PEoU→SEP	0.306 (4.175***)	0.372 (8.698***)	0.285 (6.10***)	0.066	1.301
PEoU →ENJ	0.291 (4.358***)	0.145 (4.418***)	0.198 (4.972***)	0.211	3.580***
PEoU →NOV	0.218 (3.171***)	0.543 (18.15***)	0.507 (12.826***)	-0.061	1.005
PEoU →UNF	0.302 (3.361***)	0.197 (5.167***)	0.403 (9.000***)	- 0.062	1.259
PEoU →INT	0.203 (3.419***)	0.223 (5.876***)	0.149 (3.795***)	0.089	2.027*
PU→SOC	0.521 (8.199***)	0.200 (5.468***)	0.353 (7.286***)	- 0.060	0.999
PU→SEP	0.425 (6.179***)	0.308 (6.402***)	0.307 (6.544***)	0.045	0.758
PU→ENJ	0.455 (6.179***)	0.577 (17.75***)	0.577 (17.742***)	0.024	2.56**
PU→NOV	0.392 (5.657***)	0.367 (9.653***)	0.200 (5.593***)	0.031	2.80**
PU→UNF	0.384 (3.021***)	0.489 (16.690***)	0.312 (7.118***)	0.053	3.43***
SOC→INT	0.067 (0.844)	0.123 (0.342)	0.051 (1.12)	0.046	2.030**
SEP→INT	0.059 (0.669)	0.046 (0.13)	0.072 (1.53)	- 0.043	0.657
ENJ→INT	0.314 (3.591*)	0.262 (7.767***)	0.192 (4.56***)	0.013	2.130**
NOV→INT	0.168 (2.396***)	0.208 (4.102***)	0.146 (2.87**)	- 0.042	1.241
UNF→INT	0.233 (3.22**)	0.128 (0.34)	0.167 (3.01**)	0.023	4.34**

Note(s): PEoU =Perceived ease of use; PU=Perceived usefulness; SOC=Socialisation; SEP=Self-presentation; ENJ=Enjoyment; NOV=Novelty; UNF= Unique function.

DISCUSSION AND IMPLICATION

This study provides novel insights into the motivations behind AI adoption within Iranian families, focusing on the distinct usage patterns of adolescents and their parents. By integrating the TAM and the U&G theory, our research offers a comprehensive framework that bridges the gap between functional and experiential motivations for technology use. The findings reveal significant generational differences, with adolescents demonstrating notably higher engagement with AI-powered technologies such as smart TVs, gaming consoles, smart home gadgets, AI personal assistants, and social media chatbots, compared to their parents. This pattern aligns with existing literature suggesting that younger generations are more adept at adopting new technologies, often driven by a quest for socialization, entertainment, and novel experiences (Choudrie et al., 2020; Szymkowiak et al., 2021). The pronounced preference of adolescents for interactive and entertainment-centric AI devices underscores their desire for technologies that facilitate social interaction, personal expression, and a sense of novelty. In contrast, parents often perceive AI primarily as a tool for functional tasks, highlighting a generational divide in the motivations underlying technology adoption.

The results reinforce the utility of TAM, particularly the roles of PU and PEoU, in determining users' intentions to adopt AI. These findings are consistent with prior research on AI adoption in Iran, where users have been shown to prioritize the customization and utility of AI devices to meet their unique needs (Haji Molla Mirzaei & Azizi Mehmandoost, 2024). However, our study also expands the scope of TAM by incorporating intrinsic motivations, such as socialization, self-presentation, novelty, enjoyment, and the desire for unique functionalities—elements central to U&G theory. This extension of TAM emphasizes that the adoption of AI is not driven solely by functional considerations but is also shaped by the desire for social connection, enjoyment, and personal expression. These findings align with previous studies (Kaur et al., 2020; Perks & Turner, 2019) that underscore the significance of intrinsic gratifications in technology adoption.

An unexpected finding was the lack of a significant relationship between self-presentation and novelty and the intention to use AI, which contrasts with prior research suggesting these factors play a key role in technology engagement (Ray et al., 2020). This discrepancy may stem from cultural nuances within the Iranian context, where motivations for AI use may prioritize social interaction and enjoyment over self-presentation or novelty. These insights suggest that generational and cultural variations significantly influence the underlying motivations for AI use, necessitating further exploration into how these factors manifest in different societal contexts.

From a practical standpoint, the implications of these findings are substantial for AI developers and policymakers. Given the generational differences in AI adoption, there is a clear need to design AI technologies that cater to the diverse needs of different age groups. Adolescents, who are more inclined to use AI for socialization, entertainment, and novelty, require devices that are interactive, personalized, and engaging. In contrast, parents are more likely to prefer AI tools that enhance household efficiency and are easy to use. Thus, developers should create user-friendly AI applications that strike a balance between functionality and social engagement, ensuring that both younger and older family members can benefit from these technologies. Moreover, considering adolescents' openness to diverse forms of AI, there is a pressing need for educational initiatives that promote responsible AI usage, particularly regarding its impact on social interactions and family routines.

In conclusion, this study advances the understanding of AI adoption by integrating TAM and U&G theory, highlighting the complex interplay of extrinsic and intrinsic motivations within generational and cultural contexts. By shedding light on the role of both functional and experiential factors in AI engagement, this research offers valuable insights that can guide the design and development of AI technologies that are not only user-friendly but also socially engaging and culturally relevant. Future research should continue to explore the nuanced motivations for AI adoption across diverse cultural and generational groups, further refining the models and frameworks that guide technology acceptance in family settings.

LIMITATION AND FUTURE DIRECTION

While this study offers important insights into generational patterns in family-based AI adoption, several limitations warrant attention. First, the sample is restricted to families in Tehran, which may not reflect the full range of cultural, socioeconomic, and technological variables that could affect AI adoption across broader populations. Future research could address this by including participants from both rural areas and other urban centers to enhance generalizability. Additionally, although the integration of the TAM and U&G theory provided a solid framework for understanding adoption motivations, it may not fully capture factors like privacy concerns or trust in AI that can shape generational preferences. Exploring these aspects through additional theoretical lenses could offer a more nuanced view. Lastly, as AI technology advances rapidly, longitudinal studies would be particularly valuable for tracking how motivations and attitudes toward AI adoption evolve, especially as younger generations transition into adulthood.

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