How Education and Tech Savvy Perception Shape AI Interactions*

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Abstract— **This study examines how education level and self-perceived tech savviness influence individuals' reliance on AI technologies in their daily lives. We surveyed participants (N=53) with varying educational backgrounds to assess their AI perceptions (comfort, trust, usefulness, ease of use) and habit formation around AI features. Results reveal that individuals with higher education, especially those with Master's degrees, exhibit significantly stronger reliance on AI tools. Additionally, self-reported tech savviness impacts reliance on AI-powered recommendations. These findings emphasize the interplay of formal education and self-confidence in shaping AI adoption. Designing inclusive AI interfaces and creating educational interventions tailored to diverse backgrounds are crucial for promoting AI use and unlocking its full potential for all users.**

Keywords: ***Artificial intelligence, technology acceptance, habit formation, education, self-efficacy***

I. Introduction

Artificial intelligence (AI) technologies are rapidly infiltrating various spheres of daily life, providing innovative solutions for task automation, predictive analytics, and tailored recommendations. Yet, the widespread integration of AI tools is contingent upon factors extending beyond their technical capabilities. User acceptance and the development of AI-integrated habits are vital for unlocking the full transformative potential of AI in multiple aspects of everyday life [1].

Empirical evidence suggests a complex relationship between individual characteristics, the perceived utility and potential risks associated with AI technologies, and their sustained adoption [2]. Education level is a key user characteristic that plays significant role in shaping individuals' interactions with technology [3]. Education not only equips individuals with the technical skills necessary to operate and navigate AI tools (e.g., Alexa, Siri, movies or songs rrecommendation systems i.e., Netflix, Spotify, weather prediction apps, image and facial recognition in security systems etc.) effectively, but it also cultivates critical thinking abilities and fosters a more analytical approach to technological advancements [4]. Furthermore, education can influence an individual's risk tolerance and propensity to embrace novel technologies [5]. Those with higher levels of education may be more receptive to benefits of AI and demonstrate greater willingness to experiment with new technologies, even if they are accompanied by uncertainty.

Despite its importance, there remains a paucity of research investigating the complex interplay between education level, AI acceptability, and habit formation in daily life AI technologies used. Understanding these dynamics is crucial for several reasons. Firstly, disparities in AI acceptability and habitual integration across educational groups could exacerbate existing knowledge and skill inequalities. Individuals with lower levels of education may be less comfortable using AI tools, leading to a reluctance to explore their potential benefits. This could hinder their ability to leverage AI for tasks such as information retrieval, personalized learning, or even basic productivity enhancements. Over time, these disparities could translate into broader skill gaps, further marginalizing those who lack the confidence or knowledge to integrate AI into their daily routines [6]. Secondly, this research can inform the design of inclusive AI technologies and the development of educational interventions that promote the equitable adoption of AI across a wide range of daily routines. By understanding the factors that influence AI acceptability among individuals with varying educational backgrounds, researchers and developers can create AI tools that are user-friendly, transparent, and address the specific needs and concerns of diverse user groups. Educational interventions can also play a critical role in demystifying AI, fostering a more positive perception of its capabilities, and equipping individuals with the skills and confidence to leverage AI effectively in their daily lives.

While formal education plays a role in fostering technological proficiency, it doesn't necessarily provide a complete picture of an individual's tech savviness. Emerging research suggests a potential disconnect between self-perceived technological abilities and formal education level [7]. Investigating this mismatch is crucial for several reasons. Firstly, technological proficiency develops through both formal and informal learning [8]. Informal experiences, including personal projects, self-exploration of tools, and workplace exposure, can significantly enhance technical skills alongside formal education. Secondly, individuals might overestimate their ability to navigate complex technologies, particularly newer AI-driven tools [9]. This overconfidence bias could create mismatches between perception and actual skill levels. Lastly, considering the diverse types of education individuals pursue, those without traditional STEM degrees might nonetheless possess substantial technology skills, acquired through alternative learning paths [10]. Understanding this potential gap between perception and education is crucial, as it could directly impact how individuals approach and utilize AI technologies, influencing their initial adoption and long-term engagement with these tools.

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This study investigates the complex relationship between individuals' self-reported tech savviness, their level of formal education, and their reliance on AI technologies in daily life. Early statistical analysis suggests a disconnect between how tech-savvy individuals perceive themselves to be and what their education level might traditionally suggest. This finding emphasizes the importance of both formal and informal learning experiences in developing technological skills. Importantly, the study explores how this potential difference in self-perception, possibly caused by overconfidence or underestimation, might influence the way individuals interact with AI tools. *We hypothesize that this mismatch in perception will impact reliance on AI technologies, with those overestimating their tech savviness being more likely to experiment with new AI features.* Understanding these factors has significant implications for the inclusive design of AI systems. By ensuring interfaces and educational resources cater to diverse technical backgrounds and confidence levels, we can empower users around the world to benefit from the potential of AI technologies, regardless of their formal educational background.

II. Background

The pervasiveness of AI technologies in contemporary life is undeniable. AI tools are transforming various domains, from streamlining daily tasks with recommendation systems and virtual assistants to revolutionizing industries through predictive analytics and automated processes [11]. However, widespread adoption and sustained integration of these technologies hinge on user acceptance and the formation of AI-powered habits [12]. Here, education level emerges as a critical factor influencing individuals' interactions with AI in daily life. While the technical capabilities of AI are constantly evolving, the success of AI implementations depends heavily on human factors [13]. User acceptance, bounding factors like perceived usefulness, perceived ease of use, and trust in AI, plays a pivotal role in determining whether individuals will embrace and integrate AI tools into their routines [14]. Research suggests that individuals with a positive perception of AI are more likely to experiment with new tools and persevere through initial learning curves [15]. Conversely, negative perceptions fuelled by concerns about privacy, security, persuasiveness of technology (e.g., forceful, or false advertising etc.) and potential job displacement can hinder adoption [16].

Education, encompassing both formal and informal learning experiences, shapes an individual's approach to technology in several ways. Formal educational attainment equips individuals with the technical skills necessary to navigate and utilize AI tools effectively [17]. Beyond technical proficiency, education fosters critical thinking skills and a more analytical lens through which to evaluate technological advancements [4]. Individuals with higher levels of education may be better equipped to assess the potential benefits and risks associated with AI, leading to a more informed and balanced perspective on its implementation. Furthermore, education can influence an individual's risk tolerance and propensity to embrace novel technologies [18]. Those with more education might demonstrate a greater openness to exploring unfamiliar technologies and a willingness to experiment even in the face of some uncertainty. This is because education often cultivates a more future-oriented mindset and an appreciation for the potential benefits of technological innovation [19]. It's important to acknowledge that education is not the sole determinant of AI acceptance. Individual differences in personality traits, such as openness to experience and technological innovativeness, also play a significant role [20]. Even within educational groups, individuals might exhibit varying levels of comfort and trust towards AI. Education, however, can shape these individual differences to a certain degree. By fostering critical thinking and a balanced approach to technology, education can equip individuals to make informed decisions about integrating new technologies into their lives, even if they possess a naturally cautious personality.

Beyond initial acceptance, education can also influence the formation of habits around AI use. Habit formation is a complex process involving the repetition of a behaviour, leading to its eventual automation [21]. Individuals with higher levels of education might be more adept at strategically integrating new technologies into their routines and developing consistent patterns of AI use. Their understanding of technology's potential benefits and their comfort with exploration might facilitate the transition from initial adoption to a more habitual engagement with AI tools [17, 22]. While the influence of education on technology acceptance is well-established, the specific role of educational background in shaping AI acceptability and the formation of AI-integrated habits remains under-explored. This study aims to address this gap in knowledge by investigating how education relates to user perceptions of AI, including comfort, trust, and reliance, and how these perceptions translate into daily use patterns across AI functionalities like recommendations, predictions, and assistance. Understanding these dynamics is crucial for promoting equitable AI adoption and for designing educational interventions that can empower individuals to leverage AI technologies effectively in their daily lives.

The Technology Acceptance Model (TAM) and its subsequent iterations (TAM2, TAM3, UTAUT) have been highly influential for understanding the factors shaping the adoption of new technologies [23, 24]. These models posit that perceived usefulness, perceived ease of use, and social influence are critical determinants of technology acceptance and usage intentions. In the context of AI, the TAM framework suggests that individuals with higher levels of education might perceive AI tools as more useful and easier to navigate for several reasons [25]. Firstly, their educational background likely equipped them with the technical skills necessary to understand and operate AI functionalities. Secondly, their experience with learning new technologies might cultivate a comfort level with exploration and experimentation, making them more receptive to trying out AI tools. Finally, the emphasis on technological proficiency in education systems could lead to a perception of greater social pressure or societal encouragement to adopt AI technologies, as these tools become increasingly integrated into various aspects of life and work.

Understanding how habits form can inform strategies for promoting long-term AI use is crucial. Habit formation theories, such as the Action-Outcome Framework (AOF) by Dickinson and Balleine [26], emphasize the role of positive reinforcement in solidifying behaviors. In the context of AI, the ease of use and perceived benefits of integrating AI tools into tasks can serve as positive reinforcement, making continued use more likely. Additionally, the Habit Loop model by Charles Duhigg [27] highlights the importance of cues and routines. AI interfaces can be designed to provide clear visual cues that trigger users to utilize specific AI features within their daily routines. This reinforcement, combined with regular exposure, may facilitate the development of habitual AI usage patterns among individuals with higher familiarity and comfort with technology fostered by education. While acceptance and habit formation are distinct concepts, they are inherently linked in the adoption process and long-term use of technologies. Technology acceptance models often include behavioural intention to use as a key outcome, which is a precursor to actual usage. However, the sustained integration of a technology into daily routines depends heavily on habit formation, as individuals gradually automate their interactions with technology, requiring less conscious effort.

The present study investigates how education level influences both the initial acceptance of AI technologies, shaped by core constructs of TAM and other related models, and the subsequent trajectory of habit formation. Additionally, it examines the role of self-reported tech savviness, exploring how this perception might interact with formal education. Specifically, the study investigates whether individuals with higher education levels, or greater self-assessed technological proficiency, are more likely to not only accept AI but also successfully develop regular patterns of AI usage in daily life.

Based on the outlined theoretical background, this study poses the following research questions:

1. Do individuals with different education levels differ in their perceptions of AI acceptability, including comfort, trust, perceived usefulness, and perceived ease of use?
2. Do self-reported tech savviness and formal education level interact to influence the formation of habits around AI tool usage in daily life? Do individuals with higher education levels or greater self-perceived tech savviness exhibit faster and more consistent integration of AI technologies into daily routines?

We hypothesize that both higher education levels and greater self-reported tech savviness will correlate with greater initial AI acceptability and more accelerated development of AI-related habits.

III. METHODOLOGY

The study employed a cross-sectional research design to investigate how individuals with varying backgrounds interact with and rely on AI features in their daily lives. The goal was to understand factors influencing the adoption of AI technologies, their integration into routines, and the potential impact of self-perceived tech savviness and usage habits on reliance. This research was conducted in accordance with the ethical guidelines established by the University of Sunderland, UK Research Ethics Committee. To ensure a broad range of perspectives, we recruited 53 participants through online and personal networks. Advertisements emphasized the study's focus on everyday AI experiences. Inclusion criteria focused on basic tech literacy, regular use of common devices (like smartphones, computers, smart speakers, etc.), and willingness to discuss AI interactions. This approach aimed to capture insights from individuals who regularly encounter AI, regardless of their specific technical expertise, allowing for a focus on how education level shapes perceptions and habits despite similar levels of exposure.

The online questionnaire comprised multiple sections:

- **Demographics:** Participants provided age, gender, ethnicity, education level, and location. This data explores relationships between demographics and AI feature reliance, particularly how educational background might interact with other variables.
- **Tech-Savviness:** Likert-scale items (1-7) assessed self-reported comfort and proficiency with technology, along with questions about daily AI tech usage, number/types of devices, and years of experience. To assess the role of self-perception alongside formal education, participants were asked to directly evaluate their technological proficiency with the question, "Do you consider yourself tech-savvy?" Response options included "yes," "no," and "not sure." This inclusion aimed to investigate potential discrepancies between self-assessment and education level, and how these perceptions might influence engagement with AI technologies.
- **AI Feature Use:** Specific sections on reliance:
    - **Prediction:** AI features anticipating needs (autocomplete, personalized feeds, suggested products etc.).
    - **Assistance:** AI assistants (e.g., Siri, Alexa etc.) for tasks like smart home control, reminders, information retrieval, or message composition.
    - **Recommendations:** AI-driven recommendations for products, movies, music, or other content across various platforms or streaming services.

A mixed-methods approach was used, combining Likert-scale questionnaires for ease of analysis with open-ended to gather qualitative insights (motivations, experiences, decision-making). Data were analyzed using SPSS software, and statistical analysis methods (ANOVA, T-tests, correlations) will be detailed in the next chapter.

IV. RESULT & DISCUSSIONS

Firstly, a Paired sample T-Test was made to study the relations between the participant's self-assessed tech proficiency and their education level. T-test results reveal (see Table 1) intriguing disconnect between how tech-savvy individuals perceive themselves and what their formal education level suggests about their technological capabilities. Participants consistently expressed a greater belief in their own technological proficiency (mean = 1.34) compared to their measured education level (mean = 3.47). This statistically significant difference ($p < 0.01$) is further emphasized by the large effect size (Cohen's d = -2.173). Education level was measured on an ordinal scale, with 1 representing 'High School,' 2 representing 'College,' 3 representing "Bachelor's Degree,' 4 representing Master's Degree,' and 5 representing 'PhD'.

TABLE 1: Comparison between self-reported tech-savvy and formal education level.

Measure	Mean	Sig.	Effect's Size (Cohen's *d*)	Implications
Self-assessed tech-savviness	1.34	-	-2.173 (large)	Participants perceive themselves as more tech-savvy than their education level might suggest.
Formal education level	3.47	$p<0.01$	-2.173 (large)	There is a significant gap between self-perceived tech ability and formal education

Several factors might contribute to this observed discrepancy. Firstly, technological proficiency is often developed through a combination of formal education and informal learning experiences. While formal education establishes a foundation of knowledge and skills, real-world technological fluency can be significantly shaped by factors outside the classroom. These include pursuing personal hobbies and projects involving technology, gaining hands-on experience through self-directed exploration of new tools, and being exposed to technology-driven tasks in the workplace. These informal pathways of learning can equip individuals with valuable technical skills, regardless of their formal educational background. Secondly, there's also the possibility of overconfidence bias. In today's technology-rich environment, individuals might overestimate their ability to navigate complex technological systems or adopt new AI-powered tools. While familiarity with everyday technologies can create a sense of confidence, more specialized AI-driven features might present higher learning curves. Lastly, the type of education could play a role. Those with degrees outside traditional STEM fields might still cultivate significant technological skills through self-directed learning, research-focused projects, or work experience that leverages technology in creative or analytical ways. This underscores the importance of recognizing that technological proficiency encompasses a broad spectrum of skills that can be acquired through diverse paths outside formal education alone. The mismatch between an individual's self-perceived tech savviness and their formal education level can impact their interactions with AI tools. Those who overestimate their abilities might become frustrated with complex AI or lack of clear guidance. Conversely, those who underestimate their skills due to their educational background might miss opportunities to utilize AI or lack the confidence to try new tools. The descriptive statistics and ANOVA results (Table 2) shed light on the relationship between education level and participants' overall reliance on daily AI technologies.

TABLE 2: ANOVA results on formal education level and overall reliance.

Score	*df*	Mean Square	F	Sig.
Between groups	3	1389.71	4.42	0.008
Within groups	49	314.24		

The results (see Figure 1) reveal a clear trend: participants with higher education levels tend to score higher on overall reliance on AI technologies. The average score progressively increases from College to Bachelor's to Master's degrees. This aligns with our initial hypothesis, suggesting that educational attainment might influence how readily individuals adopt and integrate AI features into their daily routines. There are several possible explanations for this observation. First, higher education may expose individuals to a wider range of technologies and foster a more positive perception of their potential benefits [29]. Second, educational programs can equip individuals with the technical skills and critical thinking abilities necessary to navigate AI tools effectively, potentially leading to a greater sense of comfort and confidence in using them [30]. This enhanced comfort level might translate into a stronger willingness to experiment with AI features and explore their functionalities in various daily tasks.

Additionally, Post Hoc analyses were conducted to further explore the impact of self-assessed tech savviness on AI reliance within specific domains. The Tukey HSD and Games-Howell tests, designed to account for multiple comparisons, revealed significant differences between groups. Notably, individuals who identified as "Tech Savvy" exhibited a significantly higher reliance on AI-driven recommendations ($p = 0.005$ for Tukey HSD, $p = 0.002$ for Games-Howell) and predictions ($p = 0.043$ for Tukey HSD, $p = 0.041$ for Games-Howell) compared to those who identified as "Not Tech Savvy." This suggests that self-perceived tech savviness plays a crucial role in shaping AI adoption patterns, particularly in areas where individuals feel more confident in their abilities. However, this effect was not observed for AI assistance or overall, AI reliance, indicating that other factors might be at play in these domains. The consistent pattern of findings across both post-hoc tests, despite the Games-Howell test's

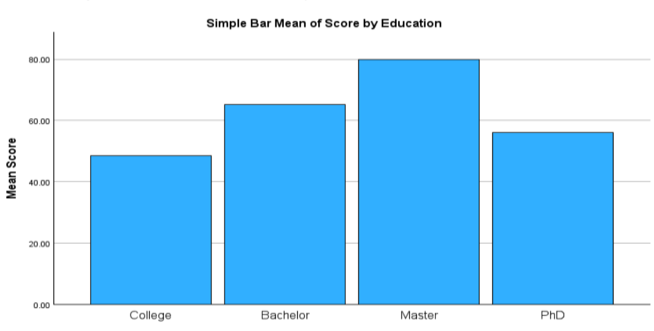

Figure 1: Mean scores of reliance based on

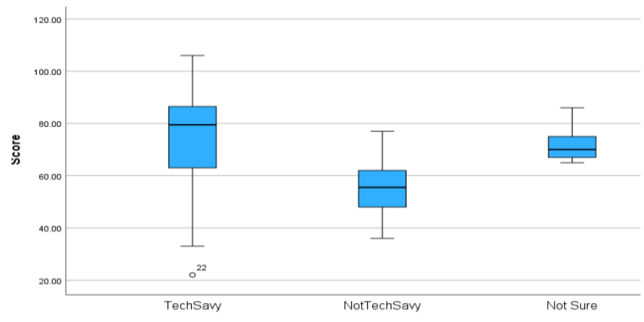

Figure 2: Boxplot showing scores of self-assed techs-savviness.

more conservative nature, reinforces the robustness of these conclusions. Additionally, a post-hoc power analysis indicated sufficient statistical power to detect these effects, further supporting the validity of the findings.

Individuals with Master's qualifications consistently scored significantly higher in overall reliance on AI features. This suggests a stronger tendency within this group to not only be aware of but also actively utilize and trust AI functionalities in various aspects of their daily lives. Their educational background may have equipped them with the technical proficiency and critical thinking skills to confidently explore and experiment with different AI features. Additionally, Master's programs often expose students to research and analysis involving cutting-edge technologies, potentially fostering a more open and trusting attitude towards AI advancements. The findings regarding College and PhD groups warrant further exploration. The College group's score is relatively close to the Bachelor's group, and some statistical tests show a non-significant difference. Additionally, the PhD group's small sample size (only two participants) makes it difficult to draw definitive conclusions compared to the Bachelor's group. Previously discussed TAM theoretical frameworks and habit formation theories offer potential explanations for these observations. Higher education might enhance individuals' perceived usefulness and ease of use of AI tools. This is due to enhanced technical skills, experience with new technologies, and confidence in troubleshooting, leading to greater comfort and willingness to explore AI features. Additionally, education can foster the development of habits around AI use, as individuals with greater comfort levels with technology may transition more easily from initial acceptance to consistent usage patterns. Their educational background may have equipped them with the ability to learn new interfaces quickly and instilled a stronger sense of self-directed learning, facilitating the exploration and integration of AI tools into their daily routines.

This results have compared with another analysis with self-assessed tech-savviness and overall reliance on technology. One-way ANOVA was performed on self-assessed tech-savviness and each type of AI tech categories (i.e., prediction, recommendation, and assist). Results showed a significant effect on reliance on AI-driven recommendations ($p = 0.012$). This means those who consider themselves tech-savvy tend to rely more on recommendations for content or products. A borderline significant effect was found with AI-based prediction features ($p = 0.05$), suggesting a possible weak relationship. Interestingly, perceived tech savviness did not significantly impact the use of AI assistants, overall reliance on AI, or the formation of AI-related habits. Effect sizes were largest for recommendations, indicating that perceived tech skills have the strongest influence on utilization in this area.

Figure 2 shows an overall view of perceived tech-savviness scores on the overall AI reliance. One key finding concerns from this analysis is the influence of perceived tech-savviness on AI-powered recommendations. Individuals who consider themselves "Tech Savvy" (mean Recommendation score = 12.23) exhibited a statistically significant ($p = 0.012$) higher reliance on AI recommendations compared to those who rated themselves as "Not Tech Savvy" (mean Recommendation score = 7.25). This 5-point difference translates to a potentially substantial variation in user behaviour. For instance, a "Tech Savvy" user might readily embrace personalized music recommendations on a streaming platform like Spotify, while a "Not Tech Savvy" user might be more hesitant, opting for manual browsing or familiar playlists.

Interestingly, the influence of perceived tech-savviness appears more nuanced when considering other AI functionalities. Factors like reliance on AI assistants (Assist score) and the formation of habitual AI usage patterns (habit score) showed no significant correlation with self-rated technology skills. This suggests that beyond perceived technical ability, additional factors influence how individuals interact with AI in these domains. Anxiety about interacting with complex AI interfaces or unfamiliarity with voice-activated assistants might deter users regardless of their self-assessed tech skills. In contrast to perceived tech-savviness, educational background exhibited a broader influence on AI adoption. Individuals with higher levels of education (potentially reflected in higher mean scores across various AI-related measures) demonstrated a greater propensity to not only utilize AI recommendations (Recommendation score) but also integrate AI more broadly into their daily routines (i.e., overall reliance on AI features) and develop habitual AI usage patterns (habit score). This difference in impact suggests that formal education equips individuals with a foundational knowledge base and critical thinking skills that extend beyond just adopting AI. Education might foster an openness to new technologies and ability to discern when and how to leverage AI functionalities effectively across various aspects of life.

V. Conclusion

The findings from the current study confirm our hypotheses and align with established frameworks like the TAM, which posits that perceived usefulness and ease of use are key drivers of technology adoption. Individuals with higher education levels, particularly those with Master's degrees, consistently demonstrated greater perceived usefulness and ease of use regarding AI technologies. This increased acceptance likely stems from the enhanced technical skills and critical thinking abilities fostered by their education. For instance, someone with a Master's degree in computer science might be more confident in evaluating the algorithms powering a recommendation system, leading to a higher perceived usefulness compared to someone with a high school diploma. Furthermore, educational experiences can equip individuals with the analytical thinking and problem-solving abilities needed to navigate and learn new technologies, increasing their perceived ease of use. This can translate into a willingness to explore different AI features and experiment with their functionalities, potentially leading to the discovery of valuable use cases that solidify into regular habits.

The results also highlight the importance of self-perceived tech savviness, particularly in the use of AI-driven recommendations. This domain might be perceived as less technically demanding compared to other AI functionalities, making it more susceptible to the influence of self-assessment. This finding underscores the need for AI design that considers the unique interplay between an individual's educational background and their perception of their technical abilities. For example, users with high educational attainment but low self-perceived tech savviness might benefit from AI interfaces that provide clear explanations alongside recommendations. This transparency can foster trust and encourage them to explore these features more confidently. Conversely, those who report strong technical self-efficacy, the belief in one's ability to perform technological tasks, might be more receptive to advanced AI features that require deeper understanding of underlying algorithms.

This study offers a novel perspective by examining the interplay between self-perceived tech savviness and formal education level in the context of AI adoption. It explores how this potential mismatch, arising from overconfidence or underestimation of skills, influences individuals' interactions with AI technologies. By investigating the impact of both formal and informal learning experiences on AI acceptance and habit formation, the research provides a deeper understanding of the factors shaping AI adoption in daily life. By closing the gap between perceived and actual ability, we can promote equitable AI adoption and maximize its potential benefits for everyone. By understanding the interplay between education and self-perception, we can design adaptive AI interfaces and educational programs that empower users of all backgrounds. Future research could explore the impact of specific fields of study and informal learning experiences on AI reliance, providing a more nuanced understanding of the diverse pathways to technological proficiency.

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