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Research Article

Embrace or resist? Drivers of artificial intelligence writing software adoption in academic and non-academic contexts

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ABSTRACT

This research investigates the perspectives of using artificial intelligence writing software (AIWS) in professional contexts, focusing on academic and non-academic writers. These two groups, while standing to gain increased productivity through the adoption of AIWS, also express concerns regarding the widespread implementation of this technology. Notably, artificial intelligence (AI) writing tech's impact on content creation has been profound, with its swift grammatically accurate content generation. This adoption, however, remains controversial. The study employs a quantitative approach, combining technology acceptance model and new computer game attitude scale. This approach allows us to discern implications of using AI-powered writing tools while accounting for possible differences in different domains of use. Through a survey of 219 participants, spanning academia and business, the study explores attitudes and willingness to use AIWS. Findings yield insights into non-academic writers' readiness and implications of AIWS adoption. Business, non-academic professionals view AIWS as a tool for efficiency and content quality, while writers in academic contexts express concerns about biases, manipulation, and job displacement. The study contributes to AIWS understanding, benefiting developers, educational institutions, and content creators, and elucidates differing attitudes and age dynamics between academics and professionals. The research underscores the multifaceted influence of AIWS, providing a foundation for future exploration in this emerging domain, as well as practical applications for industries and educational institutions.

Keywords: artificial intelligence, chatbots, ChatGPT, education, educational technologies

INTRODUCTION

Artificial intelligence writing software (AIWS) possesses the ability to learn, correct, and generate content (Popenici & Kerr, 2017) while artificial intelligence (AI) writers' market is booming. Cognitive market research forecasts the market value to reach over USD10 billion by 2030 with CAGR of 26.8% (Dharmadhikari, 2023). The widespread adoption of AIWS holds the promise of significantly enhancing professional productivity and efficiency through features like grammar checking, plagiarism detection, and language suggestions. According to a survey by The Authors Guild (2023), 23.0% of professional human writers use AI in their writing process, though mainly for grammar correction (47.0%) and brainstorming (29.0%). The objective of this study is to thoroughly evaluate the acceptance antecedents and implications towards AIWS in two connected, yet diverse groups: academic and non-academic writers. It is true that AI writing technology has emerged as influential entities within the realm of content creation, profoundly shaping its landscape (Poole, 2019). The remarkable ability of AIWS to quickly generate grammatically accurate content makes it a valuable tool for content creators (Dargham et al., 2022). However, the adoption of AI in generating content continues to be a subject of contentious debate.

On the one hand, proponents argue that AI-powered writing software automates mundane tasks, freeing up professionals' time to focus on the more creative aspects of their work (Nazari et al., 2021). This perspective highlights the potential efficiency gains associated with AIWS (Adiguzel et al. 2023). On the other hand, critics express concerns about the quality and accuracy of AI-generated content (Wagner et al., 2022). They contend that the use of AIWS may lead to a decline in content quality, raising questions about the reliability and authenticity of AI-generated work. Amidst these contrasting viewpoints, it is evident that AIWS are gaining popularity across various domains. Their ability to enhance productivity and streamline content creation processes has attracted significant attention and increased the rate of adoption. As AI technology continues to advance, it is expected that the role and impact of AIWS will continue to evolve, shaping the future of content creation and professional writing practices.

The purpose of the paper is to identify the factors contributing to the acceptance and implications of AIWS in two interconnected yet diverse groups: academic and non-academic writers. This study explores the drivers that influence adoption and the potential outcomes linked to the willingness of individuals in academic and business sectors to incorporate AI writing tools into their professional practices. To better understand the extent to which AIWS are accepted in professional settings, this study examines attitudes towards AIWS and willingness to embrace their use. The research questions guiding this study are: What factors impact the academic and non-academic groups' readiness to integrate these tools into their writing practices, and what ethical concerns or implications might arise from such incorporation?

To address this inquiry, a quantitative research approach is employed, utilizing a combination of technology acceptance model (TAM) (Davis, 1989) and new computer game attitude scale (NGGAS) (Liu et al., 2013). The research methodology involves conducting a comprehensive survey among 219 participants, comprising individuals from business and academia. This survey is designed to gather valuable insights, opinions, and firsthand experiences, thereby enabling a comprehensive understanding of the participants' readiness to embrace AIWS.

The research contributes to the existing body of knowledge by offering insights into professionals' perspectives on AI writing tools and their readiness to incorporate them into their careers and at the same time it provides a foundation for further exploration and analysis in this emerging field. Also, companies and organizations developing AIWS, or related technologies can utilize the study's findings to enhance their products and services. Understanding professionals' acceptance levels and the potential implications of widespread adoption will assist in aligning their products with the needs and expectations of the target market. Finally, educational institutions and training providers that offer writing programs or courses can also benefit from this research. The insights gained from the study can inform curriculum development and training approaches, ensuring that students are equipped with the necessary skills and knowledge to effectively navigate the evolving landscape of AI. To the best of our knowledge, no prior research has undertaken a comprehensive comparison of individuals' perceptions regarding the effectiveness, efficiency, and ethical implications of AI-powered writing tools. By investigating these unexplored aspects, this study seeks to shed light on dimensions of AIWS that have not been previously investigated. Furthermore, this study goes beyond a mere examination of general perceptions by exploring the nuanced variations that exist among industries. Additionally, the study recognizes the importance of demographic factors in shaping individuals' attitudes towards AI-powered writing tools. Using the foundation laid in the introduction as a steppingstone, the literature review examines existing research and scholarly works to provide an overview of AIWS' levels of acceptance and implications of their widespread use.

LITERATURE REVIEW

The field of writing and communication has been disrupted by AI. In recent years, AI writing services have gained significant attention as a tool for assisting professionals in writing tasks. The purpose of this literature review is to investigate the acceptance factors of AI writing software in different industries and discuss the implications of widespread use of AI writing assistance. As part of this review, relevant studies and research in the field are examined to achieve these objectives.

Acceptance Factors

Several studies have explored AI writing software's acceptance in various industries. Based on 43 contributions from experts in various fields, AI writing software is accepted differently across different industries (Dwivedi et al., 2023). While some professionals expressed enthusiasm and saw potential benefits (Adiguzel et al., 2023; Halaweh, 2023), others were more skeptical and concerned about AI's impact on their careers and primarily on teaching, learning, and academic research (Illia et al., 2022). Variations in acceptance can be attributed to factors such as the profession, individual preferences, and familiarity with AI.

The acceptance of AI writing software varies among professionals and can be better understood by categorizing users based on their characteristics and attitudes. Gkinko and Elbanna (2023) explored the use of conversational AI in the workplace to understand how employees experience and interact with these AI chatbots in their day-to-day work. They conducted a qualitative case study in a large international organization and introduced a taxonomy of users divided into four categories: early quitters, pragmatics, progressives, and persistents.

According to Gkinko and Elbanna (2023), the first category comprises "early quitters," who discontinue using the chatbot after their initial encounter. On the other hand, "progressives" are individuals who enthusiastically adopt new technologies and strive to incorporate them into various aspects of their lives. For them, utilizing technology is an integral part of their lifestyle. Another user category is the "pragmatics," who view AI chatbot as a practical tool to replace services previously provided by humans, such as an IT helpdesk. They perceive the chatbot as a means to efficiently obtain the assistance they require. Lastly, we have the "persistents," who demonstrate a resilient attitude towards AI chatbot. They continue to use it despite initial challenges and persist in interacting with it, even reformulating their questions if the chatbot fails to provide accurate responses.

The emergence of AI-powered writing tools has the potential to bring about significant transformations in the realm of academic writing. Researchers and scholars have recognized the diverse ways in which these tools can impact the writing process and enhance the outcomes in the academic domain (Alneyadi & Wardat, 2023; Halaweh, 2023). In the specific context of English academic writing, the study conducted by Nazari et al. (2021) sheds light on the positive effects of AI-powered writing tools on non-native postgraduate students. Their research findings indicate that these tools contribute to improved behavioral, emotional, and cognitive engagement among students. By helping and support throughout the writing process, AI-powered tools enhance students' self-efficacy, fostering a sense of confidence and competence in their writing abilities (Nazari et al., 2021; Seo et al., 2021). Furthermore, according to Wu and Yang (2022), the use of AI tools elicits positive emotions, creating a more favorable and motivating environment for students to engage with academic writing tasks.

In addition to the benefits experienced by students, the study by Nakazawa et al. (2022) highlights the potential of AI-based manuscript writing support for researchers. AI tools enable researchers to refine and enhance their creative output without compromising the originality of their work. By leveraging AI-based writing assistance, researchers can overcome hurdles in the writing process, such as structuring ideas or formulating coherent arguments, ultimately leading to improved academic writing quality (Kim & Kim, 2022). These studies demonstrate the potential of AI-powered writing tools to positively impact academic writing practices. The integration of such tools in educational settings can empower students, particularly non-native speakers, to overcome language barriers and enhance their overall writing skills. Moreover, researchers can leverage AI-based writing support to streamline their writing processes, optimize their creative output, and ultimately contribute to the advancement of knowledge in their respective fields (Dwivedi et al., 2023).

Many scholars have expressed concerns about the fair use of AI writing software in business, highlighting the potential challenges and implications that organizations may encounter (Else, 2023; Hutson, 2022; Munoko et al., 2020; Patel & Lam, 2023; Salvagno et al., 2023). Authenticity and human touch in AI-powered written communication have been among the primary concerns raised by Stanford scholar De Witte (2023).

Although AI writing software can create grammatically correct content, it may not provide the same nuances and personalization as human-written texts (Patel & Lam, 2023; Shing, 2022). As AI writers gain prominence, there is a risk that the personalized and human touch in communication may be compromised. Researchers argue that AI writers, while capable of generating grammatically correct and coherent content, may lack the ability to truly understand the nuanced needs and preferences of users (Atlas, 2023).

AI-generated content is still prone to errors, inaccuracies, or misleading or unsupported information, despite advances in natural language processing (Heikkilä, 2023). In the absence of human oversight and verification, businesses may suffer reputational damage or misinformation if they rely solely on AI-generated content (Chen et al., 2023). Illia et al. (2022) have raised concerns regarding plagiarism and copyright infringement when AI tools rely heavily on existing content without adequate attribution. AI writing software also has ethical implications. AI algorithms can contain biases that perpetuate discriminatory or biased language, posing legal and reputational risks to companies (Campolo & Crawford, 2020; Colleoni & Corsaro, 2022; Munoko et al., 2020).

There are also concerns about job displacement and the effects on professional writers (Laker, 2023). Businesses may rely more on automated content generation as AI writing tools become more sophisticated, possibly reducing the need for human writers (Dhiman, 2023). The loss of creativity and expertise in the field raises questions about the future of writing as a profession (Laker, 2023; Nathan, 2018). Brynjolfsson and Mcafee (2017) assert that organizations should adopt a critical and discerning approach while integrating AI writing software into their business processes, and they further recommend synergizing the capabilities of AI tools with human supervision. This combined approach ensures the preservation of quality, authenticity, and ethical considerations in written communication.

Having examined the varying levels of acceptance of AI writing software among professionals in different industries, it is crucial to understand the users of such technology. By delineating the distinct types of users and their respective behaviors, preferences, and attitudes towards AI writing software, this study provides a comprehensive framework for comprehending the diverse user landscape in the realm of AI-assisted writing. In the following section, we will discuss the implications of the widespread use of AI writing assistance, encompassing the benefits, concerns, and ethical considerations that arise from this technological advancement.

Implications of Widespread Use of AIWS

The widespread adoption of AIWS carries numerous implications for professionals and industries. Primarily, the integration of AI writing tools into various careers has the potential to enhance productivity and efficiency (Nazari et al., 2021). By leveraging AI-driven features like grammar checking, plagiarism detection, and language suggestions, professional writers can save time and streamline the writing process (Haleem et al., 2022). Another study showed that the use of ChatGPT had a positive influence on student achievement and learning in the field of electronic magnetism (Alneyadi & Wardat, 2023). Moreover, AI writing services offer valuable insights and suggestions to improve the quality and effectiveness of written communication.

Designing AI-based products to assist human writers presents practical considerations. Previous literature suggests that AIWS can impact professional copywriting, although challenges persist. AIWS have the potential to benefit professional copywriting, but it is crucial to consider the diverse goals and expertise of human writers. AI-powered writers have several potential benefits beyond improving productivity and efficiency. Using AI technology on writing and planning, scientific tasks can be completed more quickly, reducing time and effort in various fields such as biology (Coley et al., 2019) and accounting (Gulen, 2023). AI-generated content can be used for a variety of purposes, including marketing materials, reports, articles, and even social media posts. Many organizations have streamlined their content creation processes by utilizing AI-powered writers to produce grammatically correct and well-structured content with minimal human intervention (Atlas, 2023; Dwivedi et al., 2023).

Moreover, AIWS provide useful features that improve written communication in both scientific papers (Huang & Tan, 2023) and other forms of academic writing (Anson & Straume, 2022). These features include grammar checking, language suggestions, plagiarism detection, and even tone or style adjustments. It is possible for AIWS to provide immediate feedback and suggestions that will improve the coherence, clarity, and impact of written content (Cotton et al., 2023). Regardless of their English language proficiency, professionals can enhance their professional image by delivering polished and effective communication materials.

Sumakul et al. (2022) found that non-native English-speaking students perceived the use of AI positively. The latter authors' study revealed that the use of AI in education could benefit teachers and students alike. Thanks to advancements in natural language generation (Dargham et al., 2022), AI is capable of generating marketing content. A study on influencer marketing conducted by Sands et al. (2022) reveals both similarities and differences in how consumers perceive AI influencers compared to human influencers. Notably, there was no significant difference observed in terms of consumers' intention to follow or the perceived level of personalization provided by AI or human influencers. This suggests that consumers are equally receptive to following either type of influencer or perceive similar levels of personalization from both.

While AIWS excel in supporting brainstorming, story development, world-building, and research assistance, AI-powered writing assistants, as noted by Ippolito et al. (2022), struggle to preserve style and authorial voice. However, when considering professional copywriters, they tend to prioritize retaining control over their writing instead of ceding authority to AI, as highlighted by Biermann et al. (2022), who emphasize that writers seek AI companions that honor their individual values and unique writing approaches. Tang (2021) examined the effectiveness and potential impacts of automated writing (AW) technologies in business writing practices, while Dargham et al. (2022) discussed the emergence of robot writers and their potential influence on marketing and communication.

In a study by Liu et al. (2022), individuals informed about the involvement of AI in writing emails exhibited decreased trust in those emails. Qadir (2023) explored the evolving nature of engineering education in response to technological advancements and industry demands. One significant development highlighted in the study is the use of generative AI technology, exemplified by ChatGPT, a conversational AI-powered agent. The study showed that ChatGPT holds an "impressive but flawed" promise in providing personalized and effective learning experiences for students through tailored feedback, explanations, and realistic virtual simulations to facilitate hands-on learning.

The widespread use of AIWS also presents challenges and raises concerns. One significant concern revolves around the potential displacement of human writers (Makridakis, 2017). There is apprehension among professionals that the automation of writing tasks through AI may render their skills obsolete, leading to a reduction in job opportunities within the industry. As AIWS continue to advance, it is crucial to address these concerns and explore ways to ensure a harmonious coexistence between AI and human writers (Krepps & Jakesch, 2023).

Ethical considerations also come to the forefront when discussing the implications of widespread AI writing software adoption. In their New York Times article, Satariano and Mozur (2023) argue that AI-generated content could be exploited for deceptive purposes or the spread of misinformation. This is a significant ethical concern that requires careful attention. Similarly, Cotton et al. (2023) argue that safeguards and regulations must be established to mitigate these risks and ensure responsible use of AI writing tools in order to maintain the integrity of written content.

Conceptual Framework

The current study proposes merging TAM and NCGAS. TAM offers a framework to understand user acceptance and usage of technology (Scherer et al., 2019) through user's perceived usefulness (PU) and perceived ease of use (PEOU) (Malatji et al., 2020). NCGAS is a comprehensive framework for assessing the ethical implications of using AI-powered writing tools. This framework consists of three primary constructs: intrinsic motivation, trust, and social responsibility. Intrinsic motivation seeks to measure a user's internal motivation to use the tool and the user's overall enjoyment of the writing process (Liu, 2020). Trust is the user's perception of the tool's ability to produce quality output and their confidence in the reliability of the tool. Finally, social responsibility assesses the user's awareness of the tool's ethical implications, such as the potential for misuse or abuse (Horn et al., 2016). NCGAS provides valuable insight into the user's attitudes towards using AI-powered writing tools and can be used to inform the development and design of such tools.

The combination of TAM and NCGAS can provide a comprehensive measure of how professionals perceive the use of AI writers like ChatGPT. TAM measures the user's perception of the effectiveness and efficiency of the tool (Scherer et al., 2019), whereas NCGAS measures their perception of its ethical implications. This combination of measures can provide a more accurate picture of the user's overall attitude towards using the tool, as it assesses both the practical and ethical implications of the tool. Additionally, this measure can identify potential areas of improvement for the tool, such as increasing its efficiency or addressing any ethical concerns that the user may have. Through this comprehensive measure, the user can better understand their attitude towards the tool and make more informed decisions about whether or not to use it.

By thoroughly considering these implications, including the potential benefits, concerns, and ethical considerations, this study aims to make a significant contribution towards achieving a comprehensive understanding of the impact of AIWS on professionals in academia and the industry. To achieve this objective, the study employs a systematic quantitative survey that combines two models. This comprehensive methodology ensures that the findings of this study are robust, reliable, and provide valuable insights into the readiness of professionals across diverse industries to embrace AI writing tools in their careers.

METHODOLOGY

To address the inquiry regarding professionals' willingness to integrate AI writing tools into their careers, this study adopted a quantitative methodological approach. A comprehensive survey comprised 22 questions pertaining to focal constructs from NCGAS scale (adapted from Liu et al., 2013) and respondent characteristics. The three scale dimensions typically included in a TAM questionnaire (Davies, 1989) were used in the construction of this survey: cognitive (COG), affective (AFF), and behavioral (BEH). In a TAM questionnaire, the cognitive dimension focuses on the beliefs and perceptions that individuals hold regarding the technology being studied. This includes PEOU and PU. Respondents are asked to express their opinions on how easy the technology is to use and how beneficial it is in facilitating their tasks. Questions may assess perceived complexity, user-friendliness, and the utility of the technology. This dimension aims to capture the rational considerations and cognitive evaluations that influence an individual's decision to accept or reject a particular technology. The affective dimension explores the emotional responses and attitudes individuals have toward technology. While not always explicitly measured in traditional TAM scales, it can include factors such as user satisfaction and emotional responses to using the technology.

Questions may assess user satisfaction, enjoyment, or emotional reactions associated with the use of the technology. Understanding the affective dimension provides insights into the emotional aspects of technology acceptance, which can influence long-term adoption and user engagement. The behavioral dimension investigates the actual usage behavior and intentions of individuals regarding the technology. This can include measuring the intention to use and actual use behavior. Respondents may be asked about their intentions to use the technology in the future and their current usage patterns. This dimension is crucial for predicting and understanding how attitudes and perceptions translate into actual behaviors, providing practical insights into the adoption process. The survey was administered to a diverse group of professionals spanning multiple industries. The primary objective of the survey was to assess the respondents' attitudes towards AI writing software, discern perceived advantages and obstacles, and delve into their openness towards embracing these tools.

Our survey was available for a month using a multi-faceted approach to ensure comprehensive outreach. Leveraging the power of social media platforms and targeted email communication, the survey was disseminated with snowball sampling techniques. This involved initially sharing the survey link through channels associated with the research topic, such as email lists, academic announcements, social media posts in both academic and non-academic groups. Through these channels, participants were encouraged to not only take part but also to share the survey link within their networks. This organic dissemination method facilitated an expansive reach as participants forwarded the survey to colleagues, friends, and acquaintances who shared an interest in the subject matter. By harnessing the collective networking capabilities of social media and email communication, the survey reached a diverse range of respondents, thereby enhancing the inclusivity and richness of the gathered data.

Table 1. Sample characteristics

	Demographic	n	Percentage (%)
Gender	Male	100	45.7
	Female	89	40.6
	Non-binary	2	.9
	Not disclosed	28	12.8
	Total	219	100
Profession	Academic	143	65.3
	Business	76	34.7
	Total	219	100
Age	18-25 years	49	22.4
	26-35 years	55	25.1
	36-45 years	50	22.8
	46 & more	65	29.7
	Total	219	100

Snowball sampling offers several benefits in gathering data from hard-to-reach populations or those with shared characteristics (Bryman, 2016). It capitalizes on the existing social networks and connections of initial participants, leading to a ripple effect that can reach individuals who might otherwise be inaccessible through traditional methods. This approach is particularly useful when studying niche or specialized groups, where identifying potential participants is challenging. Additionally, snowball sampling allows for a diverse range of perspectives to be collected, which can enrich the data by incorporating various viewpoints and experiences.

However, there are limitations to consider. According to Bryman (2016), one potential drawback is the inherent bias introduced by relying on participants to refer others. This can result in an overrepresentation of certain subgroups within the population, as individuals with larger networks may have a greater influence on the sample composition. The method also lacks a random selection process, making it difficult to calculate the true sampling error or generalize findings to the broader population accurately. Additionally, it's important to note that the survey was only given in English language, which could further limit the diversity and representation of the participant pool. Despite these limitations, when employed judiciously and in conjunction with other sampling techniques, snowball sampling can provide valuable insights and access to unique participant groups that might otherwise remain elusive.

The inclusion of professionals from various sectors in the survey holds significant importance as it allows for a comprehensive understanding of the diverse perspectives and requirements across industries such as education, marketing, journalism, technical writing, and social media management. By examining professionals' readiness and receptiveness towards AI writing tools in these different fields, the study aims to shed light on the potential impact and feasibility of integrating such technologies into various professional contexts.

Moreover, it is equally vital to compare and contrast the views and perceptions of professionals with those of academics and students. By incorporating the viewpoints of these additional stakeholders, a holistic analysis of the potential implications and acceptance of AI writing tools can be achieved. Understanding how professionals, academics, and students differ in their attitudes towards AI writing tools will provide valuable insights into the varying needs, concerns, and expectations across these distinct user groups. This comparative analysis will contribute to a more comprehensive understanding of the potential challenges and benefits associated with the adoption of AI writing tools in both professional and educational settings.

RESULTS

In the results section, we present the findings of a study that examined the extent to which AI writing software is accepted by professionals across diverse industries and their readiness to use it. A total of 219 respondents participated in the study, including 143 academics (65.3% of the sample) and 76 professionals no longer affiliated with academia (34.7%). **Table 1** summarizes the perceptions and experiences of professionals and academics regarding the acceptance of AI writing software.

In terms of age demographics, the respondents were diverse. The largest age group represented was individuals between 46 years and older, accounting for 29.7% of the sample. The next largest age group was

Table 2. Mean, standard deviation, & correlations

Variable	Mean	Standard deviation	Alpha	CR	1	2	3	4
1. COG	3.23	.50	0.83	0.86	.733			
2. AFF	3.09	.54	0.86	0.87	.733	.881		
3. BEH	3.34	.98	0.84	0.87	.626	.629	.773	
4. Age	3.60	1.13	-	-	.733	-.192	-185	-

Note: Numbers on diagonal are square roots of average variance extracted

individuals between 26 and 35 years, comprising 25.1% of the sample. The age groups of 36-45 years and 18-25 years were also well-represented, accounting for 22.8% and 22.4% of the sample, respectively. This varied distribution of ages enables a comprehensive exploration of the potential influence of age on the acceptance and utilization of AI writing software.

Regarding gender demographics, the sample consisted of 40.6% female respondents, 45.7% male respondents, and 0.9% non-binary respondents. Additionally, 12.8% of the respondents preferred not to disclose their gender. This gender distribution ensures a diverse representation of perspectives and allows for a more comprehensive analysis of the potential influence of gender on the acceptance of AI writing software.

Taken together, the demographic information presented in **Table 1** provides a clear understanding of the composition of the sample, including the representation of professionals and academics, different age groups, and gender diversity. These demographics offer valuable insights into the potential variations in perceptions and attitudes towards AI writing software among different demographic groups, contributing to a more comprehensive analysis of the study results.

In **Table 2**, average variance extracted values are satisfactory, exceeding the 0.50 threshold, and the composite reliabilities of the constructs are also acceptable, surpassing 0.75 as recommended by Bagozzi and Yi (1988). Since our study's dependent variable relies on self-reported data, we took steps to mitigate potential common method variance (CMV) effects using a two-step approach. Initially, we ensured the survey's clarity and emphasized respondent anonymity through a pilot study, following the guidance of Podsakoff et al. (2003). Subsequently, we employed the marker variable technique for post-evaluation, as outlined by Lindell and Whitney (2001). This technique involves using a theoretically unrelated variable to the main constructs (Simmering et al., 2014). In our study, we introduced a self-efficacy scale (SES) as the marker variable. We assessed SES's correlation with the primary constructs and compared model results with and without SES. Importantly, our analyses indicated that including or excluding SES did not substantially alter the outcomes, leading us to conclude that CMV did not distort our findings, as supported by Lussier et al. (2022).

To ensure discriminant validity, it is essential to examine Heterotrait-Monotrait ratio of correlation (HTMT) (Henseler et al., 2014). When HTMT value is under 0.85, as suggested by Kline (2011), it signifies discriminant validity among constructs. In our study, all HTMT values range from 0.209 to 0.815, comfortably below the prescribed threshold. For analysis, we employed partial least squares structural equation modeling (PLS-SEM) using SmartPLS 4.09 (Ringle et al., 2022). PLS has the advantage of not necessitating normally distributed data and can effectively handle smaller sample sizes (Chin et al., 2003). Compared to covariance-based structural equation modeling, PLS-SEM, as noted by Reinartz et al. (2009), provides more robust estimations for the structural model.

A common guideline suggests having a sample size of at least 10 times the highest number of independent constructs influencing the dependent variable (Roscoe, 1975). In this study, with nine independent constructs, including control variables, the sample size of 219 meets this requirement. Additionally, we conducted a post hoc power test. The achieved power level of .99 (f^2=.08, α=.05, n=219) surpasses the recommended threshold of .80 (Cohen, 1988). The model accounts for 46.0% of the variance in BEH. To assess the model's predictive capability, we employed Stone-Geisser's Q^2. Q^2 values for BEH (Q^2=.38) and AFF (Q^2=.53) confirm strong predictive relevance (Chin, 1998) and satisfactory accuracy (Hair et al., 2019).

Given our study's contextual focus on group comparison, it is crucial to ensure measurement invariance and account for potential hidden differences before proceeding with the analysis (Hair et al., 2019). We utilized a three-step approach, following Henseler et al.'s (2016) suggestions, to assess measurement invariance using measurement invariance of composite models. In the initial step, we considered configural invariance, which

Table 3. Path coefficients

Path	β	*t*-values
COG->BEH	0.343	4.211**
COG->AFF	0.733	7.669**
AFF->BEH	0.401	4.041**
COG->AFF->BEH	0.294	4.061**
AGE×COG->BEH	-0.121	2.117*
AGE×AFF->BEH	0.085	1.596 n.s.

Note. n.s.=**=p<0.05 & *=p<0.05

Table 4. Multigroup analysis

Path	Academics		Professionals		PLS MGA	
	β_A	*t*-values	β_P	*t*-values	(β_A-β_P)	Difference *p*-value
COG->BEH	0.251	3.301	0.016	0.247	0.534**	<0.010
COG->AFF	0.141	1.874	0.093	1.299	-0.048 n.s	0.376
AFF->BEH	-0.014	0.211	0.128	2.238	-0.358*	0.032

Note. n.s.=**=p<0.05 & *=p<0.05

ensures consistent model setups, data treatment, and algorithm settings across all estimations. Subsequently, compositional invariance was evaluated through a test based on the correlation between group-specific weights of composite scores. Using a permutation-based procedure, our findings indicate the absence of compositional invariance in the dataset. In the third step, the equality of composite mean values and variances are evaluated (Hair et al., 2016). We note partial measurement invariance situation. However, since most of the effects are invariant, we conclude that the data can be pooled and subsequently used for the multigroup analysis (Henseler et al., 2016).

The study employed a FIMIX-PLS procedure to detect unobserved differences (Hair et al., 2016). Initially, considering a minimum sample size corresponding to a given R2 value, 39 is established as the minimum sample size, allowing for up to six potential segments within the dataset. FIMIX procedure is then applied to assess datasets segmented into one and two segments. However, in a three-segment solution, the relative sizes of the segments indicate that only two segments are justifiable due to the limited size of the 3rd segment (consisting of just 17 observations). Similarly, increasing the number of segments leads to insufficient representation. The fitness indices of the segment-specific solutions are examined next, with the Normalized Entropy Criterion indicating a two-segment solution as optimal. In conclusion, the findings do not support the presence of substantial heterogeneity in the dataset (Hair et al., 2016).

The results of the study reveal interesting findings regarding the relationship between cognitive factors (COG) and behavioral outcomes (BEH), with both direct and indirect influences at play (**Table 3**). The direct influence of COG on BEH was found to be positive and significant (β=.343, p<0.01). Likewise, COG exerts positive influence on BEH through AFF (β=0.294, p<0.05).

However, differences arose when comparing outcomes among various professional groups (**Table 4**). Within the academic cohort, the impact of COG on BEH was positive and significant. In contrast, this direct impact did not hold statistical significance among the professionals. Instead, in the professionals' group, the influence of COG on BEH was observed solely through its effect on emotional factors (AFF), denoted by a regression coefficient of 0.415.

Additionally, the study identified the role of age as a moderating factor in the connection between AFF and BEH, as well as in the COG-BEH pathway. Noteworthy trends came to light. Specifically, age wielded a substantial sway among professionals, whereas its impact was not significant among academics. Importantly, the age distribution was uneven between these two groups, with the academic segment being notably younger (U=3.117, p<0.01). For professionals, the interplay of age was intricate. Firstly, it exhibited a negative influence on AFF-BEH relationship. Younger respondents experienced a greater alteration in the AFF-BEH connection. The findings indicated that as respondents' age increased, the potency of AFF's effect on BEH decreased (β=-0.211, p<0.05). Conversely, age bolstered the direct impact of COG on BEH (β=0.332, p<0.01).

To learn more about how age plays a role, we split academics into two groups: those below 35 years old (young academics, 76 people) and those above 35 years old (matured academics, 67 people), as shown in **Figure 1**.

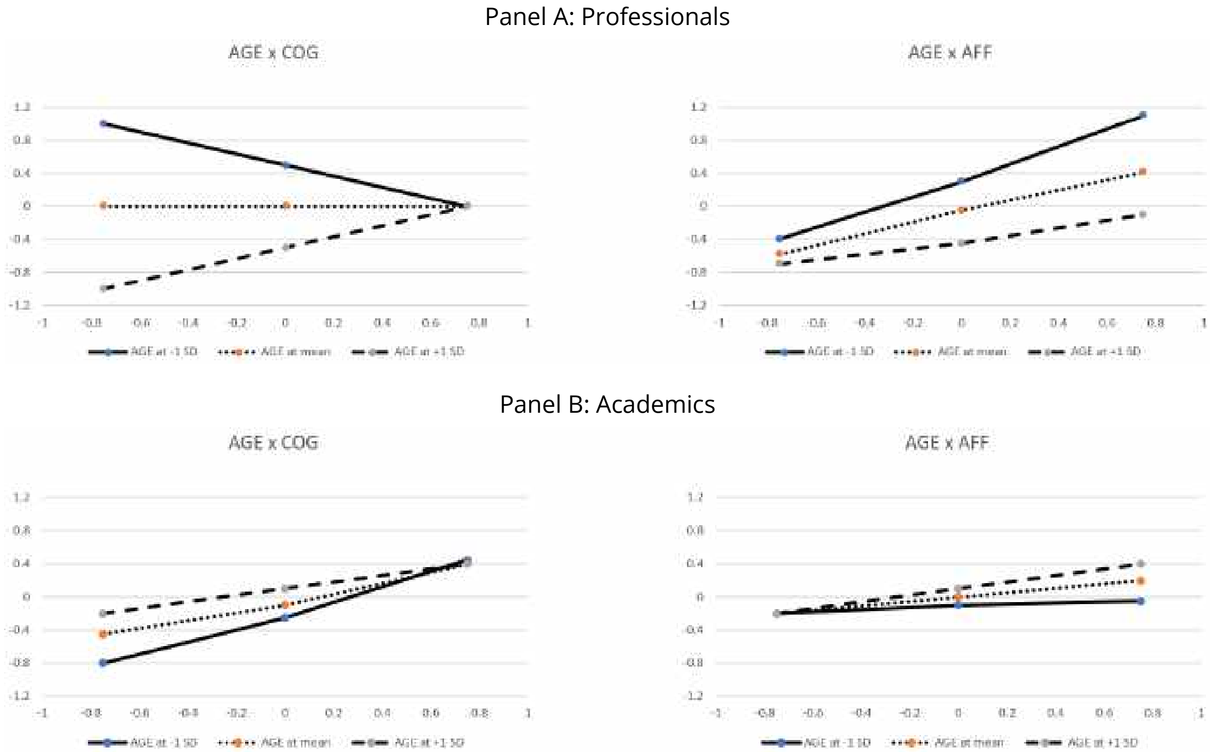

Figure 1. Moderation effect of age (Source: Authors)

The analysis of the data shows that in the first group, the connection between COG and BEH is confirmed (β=0.579, p<0.01), but there's no other indirect influence (β=-0.017, p>0.05). On the other hand, in the group of older academics, the indirect influence is important (β=0.664, p<0.01), even though the direct influence is not significant (β=0.000, p>0.05).

These findings highlight the complex interplay between cognitive factors, behavioral outcomes, and age in the acceptance and utilization of AI writing software. The stronger direct effect observed among academics suggests that their acceptance of AI writing tools is primarily driven by cognitive factors. On the other hand, professionals' acceptance is influenced by affective factors mediated by cognitive factors. Additionally, the moderation effect of age further emphasizes the need to consider age-related differences in the adoption of AI writing software, particularly among professionals. Understanding these nuanced relationships contributes to a comprehensive understanding of the factors influencing the acceptance and usage of AI writing software in different professional contexts.

DISCUSSION

Using this study as a basis, we can gain an understanding of the relationship between COG, BEH, and age when it comes to AI writing software acceptance and use. According to the findings, cognitive factors can affect behavioral outcomes directly and indirectly. Individuals' cognitive perceptions and beliefs play a crucial role in their acceptance and use of AI writing tools, as demonstrated by the direct influence of COG on BEH. Moreover, COG was found to exert a positive influence on BEH through AFF, highlighting the mediating role of emotions and attitudes in the relationship between cognitive factors and behavioral outcomes.

When comparing the results across different professional groups, interesting variations emerged. COG had a significant direct effect on BEH among academics, suggesting cognitive factors primarily drive their acceptance of AI writing software. For example, academics showed more awareness of writing's cognitive load and how AI technologies could reduce this. Meanwhile, among students, BEH had a significant direct effect on COG. This suggests their attitudes were driven by academic objectives, such as submitting a paper on time or getting a better grade.

In contrast, COG's direct effect on BEH was not significant among professionals. Instead, BEH in the professionals' group was found to be affected by COG solely through its impact on affective factors (AFF), indicating that professionals' acceptance of AI writing tools is more influenced by their emotions and attitudes, which are mediated by their cognitive perceptions. Obviously, professionals with a positive attitude toward AI writing tools were more likely to accept them. In contrast, those with a negative attitude were less likely to adopt the tools. This suggests that attitudes towards AI writing tools may be more influential than cognitive perceptions for professionals.

The study also explored how age moderated the relationship between AFF and BEH, and the path between COG and BEH. Results revealed interesting patterns, highlighting how professional writers adopt AI writing software differently based on their age. Younger professionals are more likely to be influenced by affective factors in their acceptance and use of AI writing tools when it comes to AFF and BEH. This could be due to the fact that younger professionals may be more open to new technologies and less apprehensive than their older counterparts, making them more likely to embrace AI writing software. Additionally, the study found that age increases the direct effect of COG on BEH among professionals, suggesting that as professionals get older, their cognitive factors become more influential in their acceptance and utilization of AI writing software. This is likely because older professionals have more experience with technology, have a better understanding of the potential benefits of AI writing software, and are more likely to have the resources to implement such software.

Studying the relationship between age and academics' acceptance and use of AI writing software aimed to better understand the impact of age. Participants were divided into two distinct groups: young academics, who were primarily students below the age of 25, and mature academics. Analyzing these groups revealed intriguing differences in their attitudes and behaviors towards AI writing tools.

Among young academics, mostly college students, COG influenced BEH significantly. This finding indicates that cognitive factors, such as perceptions, beliefs, and attitudes, are primarily responsible for the acceptance and utilization of AI writing tools in this group. In spite of this, the study found no significant indirect effect, indicating that affective factors mediated by cognitive factors do not play a significant role in influencing their acceptance and use of AI writing software. According to these findings, young academics' decisions to use AI writing tools are mainly rational and cognitively driven, potentially influenced by factors such as PU, PEOU, and perceived benefits.

The study found a significant indirect effect among mature academics, those over 25 years of age. Accordingly, they are more likely to accept and use AI writing software when cognitive factors mediate affective influences. As a result, emotional and attitudinal factors influence the behavior of users of AI writing applications. Emotional factors may include comfort, satisfaction, and trust in technology, as well as social norms and images associated with its use. In turn, cognitive factors play a role as mediators, shaping the relationship between affective factors and observable behavior in mature academics.

The divergence between young and mature academics in terms of their acceptance and usage of AI writing software highlights the complex interplay between cognitive and affective factors. Interestingly, young academics make decisions primarily based on rational and cognitive considerations, while mature academics make decisions primarily based on emotional and attitude factors, with cognition as a mediating factor. The ability to design and implement AIWS that respond effectively to age-related differences is crucial, as interventions and strategies tailored to a specific age group can better address their unique needs, concerns, and preferences. This is likely because younger academics are more likely to think about the immediate consequences of a decision and its impact on their career. On the other hand, mature academics are likely to consider long-term implications of a decision and how it will affect their overall life goals. Thus, AIWS should be designed to consider these differences so that they can be tailored to the needs of each specific age group.

Depending on the academic population under investigation and the specific context, the age threshold of 25 may differ. Researchers and practitioners should consider factors such as the academic level (e.g., undergraduate, graduate, and faculty), cultural differences, and the evolving technological landscape when determining age divisions for further studies. By conducting research that considers these nuanced age-related differences, a more comprehensive understanding of the factors influencing the acceptance and utilization of AI writing software among academics can be achieved, enabling the development of targeted interventions and support systems to facilitate technology adoption and integration.

In summary, these findings shed light on the complex interplay between cognitive factors, behavioral outcomes, and age in the acceptance and use of AI writing software. Confirming past studies (Haleem et al., 2023; Ippolito et al., 2022), it appears that cognitive factors play a primary role in academics' acceptance, while affective factors are mediated by cognitive factors in professionals' acceptance. Furthermore, it is likely that age also influences the acceptance and use of AI writing software, as younger academics are more likely to accept the technology than older academics. These findings suggest that both cognitive and affective factors need to be considered when assessing the potential of AI writing software to improve writing performance. AIWS are becoming more popular in academia and business settings as these nuanced relationships become clearer (Kim & Kim, 2022). As a result, the potential of AIWS to improve and streamline operations has become increasingly attractive.

CONCLUSIONS

The findings provide valuable insights into the intricate dynamics between cognitive factors, behavioral outcomes, and age regarding acceptance and usage of AI writing software. Cognitive and affective factors play varying roles in shaping the attitudes and behaviors of academics and professionals towards this technology. Academic acceptance is driven primarily by cognitive factors, such as PU, PEOU, and perceived benefits. Alternatively, professionals' acceptance is influenced by affective factors mediated by cognitive factors, demonstrating the importance of emotional and attitudinal considerations alongside rational understanding. Thus, while academics view AIWS as both opportunities and threats based on age differences, business professionals see AIWS as another tool to speed up and simplify work processes.

Similar to findings from past studies (Adiguzel et al., 2023; Dhiman, 2023), industry professionals see AIWS like ChatGPT as a valuable tool for quickly generating text, particularly in customer service and content generation. AIWS can help businesses save time and money and reduce the need for manual labor while still producing quality content (Haleem et al., 2023). AIWS can also help create content tailored to a specific audience, helping to increase engagement and conversion rates (Dargham et al., 2022). Academics view the use of AIWS with a degree of caution. They recognize that these tools have the potential to be very powerful and valuable, but they also recognize potential risks and ethical implications. These risks include the possibility of creating inaccurate, biased, or insensitive content. Additionally, there is the risk of AIWS being used to manipulate audiences or spread false information. Academics also caution that AIWS may be used to reduce the need for human labor, which could lead to job losses. Furthermore, academics stress the importance of respecting authors' rights and ensuring that generated content is appropriately attributed (Mhlanga, 2023).

Furthermore, age has been found to be a significant influencing factor on AI writing software acceptance. Compared to their older counterparts, younger academics are more likely to accept AI writing tools, suggesting a generational difference (Illia et al., 2022). In designing interventions and support systems, it is important to consider age-related differences and preferences. AIWS' potential to improve writing performance, cognitive and affective factors must be considered. The importance of understanding these nuanced relationships becomes increasingly apparent as AI-based writing tools become increasingly popular in academic and business settings. With AIWS, operations can be streamlined, and efficiency enhanced, making them a promising tool for improving writing processes.

Professional acceptance of AI writing software has significant practical implications for a variety of industries. To design AI writing software that meets the needs and preferences of its users, organizations and developers need to understand professionals' attitudes and levels of acceptance towards these tools. It is possible for developers to improve the functionality, usability, and effectiveness of AI writing tools by incorporating user feedback and addressing ethical issues. As a result, productivity, content quality, and writing processes can be improved. Organizations can also use the findings of this study to determine how AI writing tools should be integrated into their workflows to achieve the best results. By assessing the potential benefits and challenges of AI writing software, they can make informed decisions regarding resource allocation, training programs, and workflow restructuring.

The multifaceted nature of acceptance and utilization can be addressed by stakeholders by creating interventions, training, and supportive environments that take cognition, affective, and aging factors into account. This is why a comprehensive approach to AIWS could maximize its benefits and contribute to improved writing performance across a variety of settings. Future research can build upon this study's findings by employing qualitative research methods to explore professionals' attitudes and perceptions in greater depth. In-depth interviews, focus group discussions, and case studies can provide rich insights into the specific concerns, challenges, and opportunities professionals encounter when incorporating AI writing tools into their careers. Such studies and taxonomies (Gkinko & Elbanna, 2022) can explore the experiences of professionals across different industries and job roles, uncovering valuable nuances and identifying best practices for successful implementation.

Further, longitudinal studies can be conducted to determine the long-term effects of integrating AI writing software into professional practices. Through these studies, professionals can gain a comprehensive understanding of the evolving dynamics between AI writing tools and socially responsible AI algorithms (Cheng et al., 2021). Additionally, research can examine the ethical implications of AI writing software, including transparency, accountability, and biases within algorithms. A better understanding of the ethical considerations associated with AI writing tools will allow guidelines and standards to be developed so these technologies are used responsibly and ethically.

Future research studies should continue to examine professionals' attitudes toward AI writing software, address their concerns, identify best practices, and develop frameworks for effective integration. By leveraging the advantages of automation while preserving human creativity and expertise in the writing process, this ongoing research will shape the future of AI writing tools.

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