8-2024

Examining the Theory of Planned Behavior as an Explanation for Why Some Creatives Learn to use Generative AI Tools

Navrose Bajwa

Abstract

Artificial Intelligence (AI) can create art which earlier was restricted to humans. This involvement of AI in creating art poses risks of automation for the arts and design industry. One way with which artists can respond to this threat is to engage in proactive coping behavior and learn to use generative AI (GAI) for their work. Using an expanded version of Theory of Planned Behavior, this study looked at the predictors of graphic designer's intentions to learn how to use GAI for art and design work. It was hypothesized that attitudes, social norms, perceived behavioral control and automation awareness would be predictors of intention to learn GAI for art and design. An online questionnaire was developed and the final sample size consisted of 119 graphic designers. As hypothesized attitude, subjective norms and perceived behavioral control were significant predictors of intentions to learn how to use GAI, while automation awareness was not a significant predictor of intentions. The findings of this study provide an understanding of graphic designers' decision making towards learning GAI.

Keywords: Theory of Planned Behavior, Generative AI, Automation Awareness, Creatives

MONTCLAIR STATE UNIVERSITY

Examining the Theory of Planned Behavior as an Explanation for Why Some Creatives Learn to use Generative AI Tools

By

Navrose Bajwa

A Master's Thesis Submitted to the Faculty of

Montclair State University

In Partial Fulfillment of the Requirements

For the Degree of

Master of Arts

August 2024

College of Humanities and Social Sciences

Psychology Department

Thesis Committee:

[redacted]

Kevin Askew, PhD
Thesis Sponsor

[redacted]

Michael Bixter, PhD
Committee Member

[redacted]

Cheryl Gray, PhD
Committee Member

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Acknowledgements

First and foremost, I would like to extend my deepest gratitude to my mentor, Dr. Kevin Askew. His kindness, support, and patience have been invaluable throughout this journey. Dr. Askew's guidance has not only enhanced the quality of my work but also inspired me to aim for the highest standards in all my endeavors. His guidance has been a cornerstone of my success, in shaping my work and for that, I am profoundly thankful. I am also immensely grateful to my dearest committee members, Dr. Michael Bixter and Dr. Cheryl Gray. Their unwavering support, patience, and expertise have made this thesis experience incredibly positive.

Lastly, I would like to extend my heartfelt thanks to all the graphic designers who participated in my study. Their willingness to take time out of their busy schedules to complete my survey was crucial to the success of my research. I deeply appreciate their contributions and the insights they provided.

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Examining the Theory of Planned Behavior as an Explanation for Why Some Creatives Learn to use Generative AI Tools

Human expression, information transfer and storage began with art in the caves. The earliest known human art consists of zig zag patterns (Henshilwood et al., 2002 as cited in Morriss-Kay, 2010). Presently we find ourselves in a new era of technology, where artistic expression is not limited to humans. Artificial Intelligence (AI) can create art in seconds without requiring laborious amounts of time and human effort. Research has found these AI-generated artworks to be indistinguishable from human artwork (Samo & Highhouse, 2023) and even capable of winning contests (Knibbs, 2023). While the speed and quality of AI generated art are fascinating, they also present a caveat: the potential for automation in the arts and design industry. A report by Goldman Sachs predicts a loss of 300 million jobs to AI (Kelly, 2023). This threat is not only relevant at organizational level but also impacts people working in these industries, necessitating immediate research to better support and equip them to survive in this automation era.

Technological changes have been identified as an antecedent to job insecurity (Lingmont & Alexiou, 2020; Shoss, 2017). People can respond to job insecurity in four major ways. Firstly, people can respond via stress-related mechanisms and view job insecurity as a stressor leading to many negative consequences, including poor well-being, performance, anxiety, reduced creativity and counterproductive work behaviors. Secondly, people can respond via social exchange-related mechanisms – in these incidences job insecurity hinders the exchange relationship between employee and employer, leading to ill-being and diminished job attitudes. Thirdly, when the job threat has not occurred, people sometimes engage in job preservation strategies like putting extra efforts to get recognized, engaging in behaviors aligning with organizational values and being willing to work for lower wages and longer hours. Lastly, when job loss is uncertain, people sometimes engage in proactive coping – a future oriented approach that involves taking steps to mitigate the threat before it occurs. This could include networking, being aware of the job market, increasing savings, and pursuing educational opportunities (Shoss, 2017).

Proactive coping is considered the most positive outcome among the four mentioned. It is related to happiness and lower levels of depression (Stiglbauer & Batinic, 2015). Aspinwall & Taylor (1997) identified various benefits of proactive coping. Since the job threat is only a possibility, proactive coping helps lessen its impact before it occurs. The resources required to tackle the threat before it occurs are less as compared to dealing with it in real-time. Proactive coping can also lessen chronic stress experienced in anticipation of the job threat. Behaviors such as learning new skills that arise from proactive coping can lead to perceived employability enhancing perceptions of control and eventually lessens perceptions of insecurity (De Witte et al., 2015; Koen & Parker, 2020).

In the arts and design sectors, one way for artists to proactively cope with automation risk is to pursue educational opportunities and to learn to use AI for creating art and design work. They can adopt AI into their own skill set to reach new levels of artistic expression, a collaboration between AI and humans termed “augmented creativity” (Vinchon et al., 2023). Research has shown that AI-produced artistic products enhance perceptions of process novelty. Thus, artists who learn how to use AI can benefit from its speed, efficiency and resources (Moura et al., 2023). Outside the art and design industry, AI collaboration has been positively related to career satisfaction, task performance and creative performance (Kong et al., 2023).

Therefore, it is reasonable to expect that proactive coping, in the form of learning AI tools, could also be beneficial for creatives.

Given how quickly AI is advancing in the creativity industry, and the potential benefits of proactive coping strategies for creatives, it is important to examine the factors influencing artist's decisions to learn how to use AI for art and design work. Understanding these factors could help identify the antecedents to proactive coping in general and shed light on factors facilitating human-AI collaboration to augment creativity specifically. This understanding would aid in building theory around proactive coping and help create interventions to motivate artists to gain new professional skills and increase their employability.

The present study aims to develop and test a model of artist's decisions to learn how to use Generative AI (GAI) for creating art. After reviewing the literature on proactive coping and the adoption of technology, we concluded that the Theory of Planned Behavior (TPB), possibly slightly modified, could be a valid model of proactive coping for creatives facing AI automation. The TPB has been shown to be a valid model for explaining adoption of technology in general (Salleh & Laxman, 2015; Hou et al., 2022; Teo & Tan, 2012) and its three antecedents have been shown to be predictors, or conceptually related to predictors, of proactive coping. The following sections will review the proactive coping process and the relevant literature to gain a precise understanding of the behavior our model aims to predict – learning to use GAI tools for creative purposes. We will then review why the TPB might be an appropriate model and how it could be applied to creatives learning GAI. Finally, we will discuss a potential deficiency in the TPB for explaining the adoption of GAI and how awareness of automation can be integrated into the model to address this deficiency.

Proactive Coping

Aspinwall and Taylor (1997) defines proactive coping as, "efforts undertaken in advance of a potentially stressful event to prevent it or to modify its form before it occurs" (p. 417). For uncertain work environments like expiring employment contracts, proactive career behavior has been found to lessen experience of insecurity (Koen & Parker, 2020). Proactive coping can take the form of career planning, scenario thinking, career consultation, networking, reflecting and skill development (Langerak et al., 2022; Koen & van Bezouw, 2021; Koen & Parker, 2020).

The proactive coping process by Aspinwall and Taylor (1997) delineates five stages that help in effectively managing stress. Proactive coping starts with resource accumulation where individuals build skills and assets in anticipation of potential stressors. This includes reserving temporal, financial and social resources that will eventually prepare the individual to face the stressors upon their emergence. Subsequently, individuals engage in attention-recognition, which is detection of potential stressors, anticipating stressful events by screening the environment for threats and being sensitive to internal cues and signals. During the initial appraisal, the individual makes preliminary assessments by defining the stressor and its outcome. Based on the initial appraisal, the individual takes preliminary coping action that involves cognitive or behavioral activities to mitigate or combat the effects of a potential stressor. Following this, the elicitation and use of feedback is the final stage where individuals modify the initial proactive coping effort if needed by acquiring and utilizing feedback on stressor's progression and their coping effort (Aspenwall & Taylor, 1997). The process has been shown to accurately describe how proactive coping occurs in a wide variety of circumstances including older adults to understand and create interventions for management of potential stressors and heavy women to handle discrimination (Ouwehand, 2005; Bode et al., 2006).

Various studies have identified key antecedents of proactive coping which includes both psychological characteristics and contextual factors. For example, during organizational change, resilience and perceived organizational support (POS) have been proposed to enhance proactive coping (Mukerjee et al., 2021). When individuals perceive strong support from their organization, they may feel that important others (e.g., the employer, supervisors) approve of and support their engagement in proactive coping strategies. This perception can increase the likelihood of engaging in such behaviors. Furthermore, individual traits such as optimism, self-esteem and mindfulness also play a role in influencing proactive coping (Tuan, 2022; Wanberg, 1997). Optimistic individuals are likely to have a positive evaluation of their ability to manage future stressors, driving them towards proactive coping behaviors. Mindfulness could enhance awareness of benefits associated with proactive coping. Finally, perceived control reflecting an individual's sense of control over their circumstances, has been linked with proactive behaviors like job search activities (Wanberg, 1997). People who perceive high control are more likely to engage in proactive coping by searching for new job opportunities before their current job becomes unstable. Collectively, these antecedents suggest that proactive coping is influenced by a combination of internal beliefs and external factors.

Theory of Planned Behavior

Theory of Planned Behavior (TPB) is a behavior-oriented model that identifies determinants of an individual’s behavior within a particular context, rather than looking at broad psychological traits or global dispositions. According to this model, intentions serve as the central and proximal determinant of behavior. These intentions to perform a behavior are themselves driven by three key factors namely attitude towards the behavior, subjective norms and perceived behavioral control.

Attitudes towards a behavior are determined by an individual's beliefs about the outcomes of the behavior, combined with the subjective probability that these outcomes will occur. In this model, an attitude refers to the degree to which a person has a favorable or unfavorable evaluation of the behavior in question (Ajzen, 1991). For example, if someone believes that using a new technology will enhance their work efficiency (*behavioral belief*) and feels confident that this improvement is likely (*subjective probability*), they will generally hold a positive attitude towards adopting this technology. The more positive and likely the outcomes of a behavior are perceived to be, the more favorable the attitude towards engaging in that behavior (Ajzen & Kruglanski, 2019).

Subjective norms reflect the perceived social pressure to perform or not perform the behavior. This component is shaped by normative beliefs, whether important others (like family, friends, or colleagues) are performing the behavior (*descriptive norm*) and whether they approve or disapprove of the behavior (*injunctive norm*). The influence of these norms depends significantly on the importance of these referents to the individual (*referent's importance*). If a person perceives that people they respect and care about think they should engage in a behavior, this perception creates a social pressure that can strongly influence their intentions (Ajzen, 1991; Ajzen & Kruglanski, 2019).

Perceived behavioral control involves the perceived ease or difficulty of performing the behavior, influenced by past experiences and anticipated obstacles. This component of TPB captures how much control an individual feels they have over performing a behavior. It combines *control beliefs*, assumptions about the factors that may facilitate or impede behavior with *perceived power*, the perceived capacity to overcome these impediments. For instance, if an individual feels that they have the necessary resources and opportunities to learn and use a new piece of technology, despite potential challenges, they are more likely to develop a strong intention to do so (Ajzen, 1991; Ajzen & Kruglanski, 2019).

The TPB has proven to be a robust model for understanding and predicting technology-related behaviors. It has been applied effectively across various domains such as technology-enabled learning, where teachers' adoption of technology is influenced by their attitudes, institutional norms, and their ease with technology (Hou et al., 2022; Teo & Tan, 2012; Salleh & Laxman, 2015). In e-commerce, Wang et al. (2022) demonstrated how consumer behaviors in online shopping are shaped by similar factors. The framework also extends to the workplace; behaviors like cyberloafing and instant messaging (Askew et al., 2014; Lu et al., 2009) have been successfully modeled with the TPB. These applications demonstrate TPB's applicability in the digital age and suggest it might be a suitable choice for our current study involving technology adoption.

A second line of reasoning supports the TPB as a potentially valid model to explain adoption of GAI by graphic designers. As previously mentioned, adoption of GAI is an example of proactive coping. Several antecedents of proactive coping, specifically perceived control, optimism and perceived organizational support (POS) have conceptual connections to the antecedents in the TPB model.

Perceived control, a predictor of proactive coping (Wanberg, 1997), aligns directly with one of the TPB antecedents, Perceived Behavioral Control. This suggests that graphic designers who feel confident in their ability to use GAI and believe they have control over its implementation are more likely to adopt this technology.

Optimism, another predictor of proactive coping (Wanberg, 1997), parallels the TPB antecedent of attitudes. Optimism involves believing in favorable outcomes, which is conceptually similar to having a positive attitude towards a behavior. Although not identical, it is possible that more optimistic people are likely to have positive attitudes towards adopting new technologies like GAI, anticipating beneficial outcomes from their use.

POS corresponds with the TPB's subjective norms. POS reflects the approval and support of important others within the organization, thereby encouraging the adoption of proactive behaviors such as using GAI (Mukerjee et al., 2021). In short, the conceptual connections between proactive coping antecedents and TPB predictors - perceived control with perceived behavioral control, optimism with attitudes, and POS with subjective norms - suggest that the TPB might be a valid model of understanding adoption of GAI by graphic designers.

Given that the TPB might be a useful framework for understanding why creatives learn AI tools, it is important to explore how TPB constructs manifest in this context. What is the nature of the antecedents in the context of learning how to use GAI? Graphic designers may perceive learning to use GAI as beneficial for their work. They might believe that GAI can expedite the generation of creative ideas and visuals, save time, simplify tasks, and enhance work efficiency. This positive attitude toward GAI, seeing it as a tool that can significantly improve their professional capabilities, can influence their intention to adopt and learn the technology. Conversely, if they perceive GAI as harmful to their work such as leading to a loss of originality in their design, or raising ethical concerns, this negative attitude might deter them from adopting and learning it. The influence of significant others like peers, industry leaders, and influencers in the field of graphic design can play a critical role. If these significant others view the use of GAI for art and design as appropriate and beneficial, it can create social pressure that makes a designer more inclined to adopt the technology. Conversely, if significant others disapprove, these views can discourage designers from adopting the technology.

Additionally, a designer's perceived behavioral control can shape their learning intentions. If they feel confident about having sufficient time and resources to master GAI (like navigating any technical complexity or access to software), their perceived control over the situation will be high. This strong sense of control can enhance their belief that they can successfully integrate GAI into their workflow. On the other hand, if there are perceived barriers (like lack of training opportunities, high costs or lack of time), these can significantly lower their perceived control, thereby weakening their intention to adopt GAI.

Expanding the model: Automation Awareness

While the TPB has been shown to be a valid model of many different behaviors, there have been times when the model has been valid but still deficient in fully explaining a behavior. Indeed, this is why Ajzen (2020) states that the TPB is open to expansion by addition of constructs that might influence intentions and behaviors. For example, Koh et al. (2017) extended TPB to investigate behaviors related to playing augmented reality games while walking, adding constructs like automaticity, immersion and enjoyment to better understand the behavior. Similarly, Kim et al. (2013) applied TPB to the selection of eco-friendly restaurants, possibly incorporating anticipated regret as an additional factor influencing behavioral intentions.

There is reason, we believe, to suspect that the TPB might benefit from the addition of another predictor when trying to explain GAI adoption. As mentioned previously, GAI adoption is a proactive coping strategy that will be necessary in the future for staying competitive in workplaces with ever-changing technological advancements. An important part of the proactive coping process as described by Aspenwall & Taylor (1997) is the person in question's recognition and awareness of an incoming threat. This awareness enables individuals to prepare and adapt their strategies in advance, a crucial aspect that TPB does not account for. This gap highlights the need to expand the TPB model to include a variable that captures this awareness, thereby enhancing its applicability in predicting proactive behaviors like GAI adoption.

One such variable as demonstrated by research is Automation awareness. Innocenti & Golin (2022) demonstrated that workers who perceived a higher risk of their jobs being automated were more inclined to pursue additional training outside their current employment. This finding suggests that awareness of potential job automation acts as a motivator for individuals to seek new skills to enhance their employability. Thus, it becomes evident that integrating automation awareness as an additional predictor in the TPB model could significantly enhance its predictive power in contexts requiring proactive adaptation. By incorporating this factor, the TPB can be more effectively applied to study behaviors like a graphic designer's intention to learn and utilize GAI. Thus, we propose augmenting the existing TPB framework with automation awareness to better explain and predict proactive coping behaviors among professionals facing technological disruptions.

In our augmented TPB model, automation awareness serves as a fourth predictor of intentions. This construct represents an individual's recognition and understanding of the extent to which their current or future job roles might be impacted by automation. Automation Awareness enhances this model by serving as a direct predictor of intentions. It captures a critical external factor, the perceived risk of job automation, that can strongly motivate individuals to adapt their behaviors proactively. For example, a graphic designer who is aware that elements of their job might be automated may be more motivated to learn and incorporate Generative AI (GAI) into their skill set to stay relevant and competitive.

Current Study

The current study aimed to examine the factors that influence graphic designer's intentions to learn to use GAI tools as a way to augment their creativity. This investigation is particularly crucial as it addresses the proactive coping strategies designers might employ to manage automation risks and remain competitive in their field to keep up with technological advancements. Since the TPB has explained intentions in various contexts, including technology adoption, it is reasonable to think that the TPB could effectively examine graphic designers' intentions to learn GAI for their art and design work. We hypothesize that designer's decisions to engage in learning GAI are influenced by attitudes, social norms, and behavioral control. Additionally, considering the connection between threat awareness and proactive coping, we propose that awareness of automation within the graphic design field will also be a key factor in shaping designer's intentions. Our specific hypotheses are stated below and shown visually in Figure 1.

H1: Behavioral beliefs predict attitudes toward learning GAI tools for art and design.

H2: Normative beliefs predict subjective norms.

H3: Control beliefs predict perceived behavioral control.

H4: Attitudes predict intentions to learn GAI tools for design.

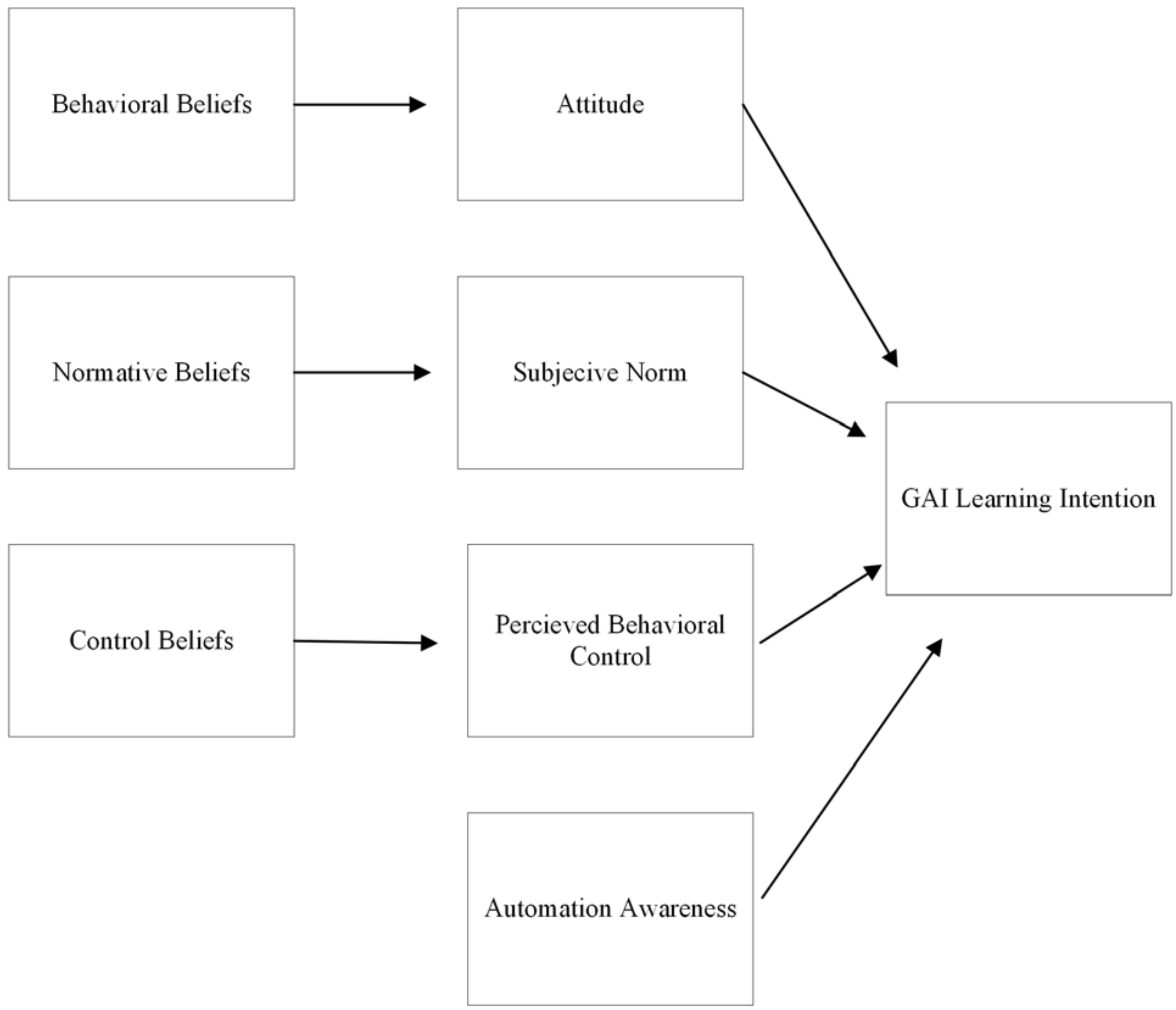
H5: Subjective norms predict intentions to learn GAI tools for design.

H6: Perceived behavioral control predicts intentions to learn GAI tools for design.

H7: Awareness of automation will explain additional variance beyond the TPB variables.

Figure 1

The augmented model of theory of Planned behavior as applied to the current study



Methods

Pilot Study

An elicitation study was conducted on a sample of 22 graphic designers using the guidelines provided by Ajzen (2019). The study elicited readily accessible beliefs about intentions to learn how to use GAI tools for art and design work using an open-ended questionnaire. Specifically, the questionnaire asked to list the advantages and disadvantages of learning to use GAI, the individuals or groups who would approve or disapprove of their learning to use GAI, the individuals or groups who themselves would most likely or least likely learn how to use GAI, and the factors that would facilitate or hinder from learning how to use GAI. A content analysis of the responses was conducted to determine the most frequent themes in terms of behavioral outcomes, normative referents, and control factors. The most frequent responses cited by at least 15% of the participants were used to create items used in the main study (La Barbera & Ajzen, 2020).

Main Study

Participants

We recruited graphic designers using various online platforms. The final sample consisted of 119 graphic designers. These participants had an age range of 18 to 67 years old ($M = 28.25$, $SD = 7.25$). Participants included more males than females (59.7% male), were predominantly full time (62.2%) and most held a bachelor's degree (59.7%).

Measures

All measures are provided in Appendix A.

Demographic information. Demographic information collected included gender, age, type of employment, and highest completed level of education.

Behavioral Beliefs. Participants rated each of the behavioral beliefs from the elicitation study in terms of its perceived likelihood (e.g. 'If I learn to use Generative AI tools for art and design work in the near future, it will help me quickly generate ideas', scored 1 = Unlikely to 7 = Likely) and its subjective value (e.g. 'How valuable are each of the following to you in the near future? - Quickly generating ideas', scored 1 = Slightly Valuable to 7 = Extremely Valuable). The perceived likelihood of each outcome was multiplied by its subjective value and the resulting products were summed for the 15 elicited behavioral beliefs identified in the pilot study.

Normative Beliefs. Normative beliefs can be composed of both injunctive normative beliefs and descriptive normative beliefs (Ajzen & Kruglanski, 2019). Thus, both types of beliefs were used to capture this construct. Participants rated each of the normative reference groups from the elicitation study in terms of their likelihood of providing approval (e.g. 'How likely do you think that the following people would approve of your learning to use generative AI tools? - Design Professionals', scored 1 = Unlikely to 7 = Likely) and the value of that approval (e.g. 'How much do you care whether each of the following people approve or don't approve of what you do? - Design Professionals', scored 1 = Not at all to 7 = Very Much). For each referent, perceived likelihood of approval was multiplied by the subjective value of approval and the products were summed separately for the five injunctive normative beliefs and six descriptive normative beliefs elicited in the pilot study.

Control Beliefs. Each of the control factors influencing learning to use GAI identified in the elicitation study were rated for the extent to which they would expect in the near future (e.g. 'Do you expect to have the following in the near future? - Access to reliable generative AI tools', scored 1 = Unlikely to 7 = Likely) and the value of that factor (e.g. 'Having the following would enable me to learn using generative AI tools for design work - Reliable generative AI tools', scored 1 = Unlikely to 7 = Likely. The perceived likelihood of each control factor was multiplied by its value and the resulting products were summed for the six elicited control beliefs identified in the pilot study.

Attitude. Attitude towards learning how to use GAI were assessed by asking participants to rate "For me learning how to use generative AI for art and design work in the near future would be…": on five bipolar adjective scales (e.g., 1 = Unpleasant to 7 = Pleasant). Responses were aggregated into a composite measure by averaging the scores on the five scales. Higher values indicate more positive attitudes.

Subjective norm. Subjective norm towards learning how to use GAI was assessed by averaging degree of agreement with four items (e.g. 'Most people who are important to me approve of my learning how to use generative AI for art and design work in the near future.'), each scored 1 = Disagree to 7 = Agree.

Perceived behavioral control. Four items were used to measure perceived behavioral control (e.g., 'I am confident that I can learn how to use generative AI for art and design work in the near future'), each scored 1 = Disagree to 7 = Agree. Responses on the 7-point scales were averaged. Higher values indicate higher perceived control.

Intention. To assess participants' intentions to learn how to use GAI, we used four items (e.g., 'I intend to learn how to use generative AI for art and design work in the near future'), each scored 1 = Disagree to 7 = Agree. These were averaged across items to produce a single composite score, with higher values indicating a more favorable intention.

STARA awareness. Automation awareness was assessed using the measure of STARA awareness created by Brougham & Haar (2018). It captures the degree to which employees believe their jobs could be replaced by technologies such as Smart Technology, Artificial Intelligence, Robotics and Algorithms. Participants were asked to consider their current job and respond to the four statements (e.g., 'I think my job could be replaced by STARA'). Responses were measured on a five-point likert scale ranging from "Strongly Disagree" to "Strongly Agree."

Procedure

Approval for the study was obtained from the University's Institutional Review Board (IRB). The Internet was used to recruit participants to complete an online questionnaire using LinkedIn and Reddit. A post sharing the information about the study was shared on these two platforms. Participants were invited to follow a link to an online questionnaire created using the Qualtrics survey platform. The first page of the questionnaire provided additional information about the study and included an informed consent statement.

To increase data quality, we followed guidelines by Ward and Meade (2023) and Goldammer et al., (2020) aimed at dealing with careless participant responses in survey data. Specifically, we (a) increased respondent motivation during the conduction of the survey by using the following two types of incentives which were listed on the social media post and on the first page of the online questionnaire – first 50 participants to get $5 amazon gift cards and a raffle of 10 amazon gift cards worth $25 each , (b) placed central items at the beginning of the survey, and (c) used instructed response items and bogus items to screen for careless responding.

In total, 268 graphic designers consented to participation in our online questionnaire. Those whose survey completion time was less than 500s and/or failed to pass three attention checks out of the four attention checks in the survey were excluded from the analyses. 500 seconds was chosen because it was determined to be the fastest someone could complete the survey if they were paying attention based on the pilot data. 119 participants met these requirements and were included in our analyses.

Missing Data

The overall level of missing data in the dataset for this study was quite low, with the average missing data proportion being approximately 0.56% and the maximum missing data proportion being 10.92%, found in only one column. Since the missing data was <5%, the choice of method to deal with the missing data would not have made much difference (Kline, 2015). To maximize statistical power with all the available information while obtaining unbiased parameter estimates, missing values were recovered using multiple imputations (MI) at the item level. In RStudio, we used the mice package (Van Buuren & Groothuis-Oudshoorn, 2011) to conduct MI using predictive mean matching (PMM). Five complete datasets ($m=5$) were generated, which were further aggregated into a single dataset (Graham et al., 2012).

Results

Table 1 displays mean, standard deviations, reliabilities of the study variables as well as correlations among these variables. Scales generally showed acceptable to excellent reliability, with alpha values ranging from .69 to .94, suggesting that pilot testing was successful at developing internally consistent scales. Specifically, the Control Belief scale demonstrated excellent reliability ($\alpha = .94$), while the STARA scale showed the lowest, yet still acceptable, reliability ($\alpha = .69$).

Table 2 shows the distribution of responses in the STARA scale. Overall, the data indicate substantial concern among respondents about the potential impact of STARA on their job security. Approximately half of the respondents express agreement or strong agreement to the statements reflecting concerns about job replacement, both personally and within their organization and industry. A smaller but significant portion of respondents disagrees or strongly disagrees, while a notable number of respondents remain neutral, highlighting the mixed perceptions and uncertainties surrounding the impact of automation and robotics on employment.

As expected, intention correlated significantly with TPB antecedents of attitude (r = 0.67), subjective norm (r = .82), and perceived behavioral control (r = .71), as well as with all belief composites. In addition, these three antecedents to intentions significantly correlated with their corresponding belief composites (*r's* = .56, .71, and .8 for attitudes, subjective norms, and control beliefs, respectively). Contrary to expectations, STARA was not significantly correlated with intentions.

Path analysis was used to formally test the seven paths of the hypothesized model (scale scores were used in the path analysis; Figure 2). The hypothesized model was based on full mediation and specified the following: Intentions (endogenous variable) were predicted by Attitudes, Subjective Norms, Perceived Behavioral Control and STARA (exogenous variables), Attitudes were predicted by Behavioral Beliefs, Subjective Norms were predicted by Normative Beliefs and Perceived Behavioral Control were predicted by Control Beliefs. Since the data failed assumptions of non-normality, we used Maximum Likelihood and Robust Standard Errors (MLR) as the estimation method as it is less sensitive to non-normality (Yuan & Bentler; 2000). Path analyses were conducted using the *lavaan* package with version 0.6-15 (Rosseel, 2012). All reported values are standardized path coefficients.

The first set of three hypotheses focused on the relationship between beliefs and the traditional TPB antecedents. Hypothesis 1 stated that behavioral beliefs would predict attitudes toward learning GAI tools for design. This hypothesis was supported, with behavioral beliefs significantly predicting attitudes ($\beta = 0.56$, $p < 0.001$). Hypothesis 2 stated that normative beliefs would predict subjective norms. This hypothesis was supported, with normative beliefs significantly predicting subjective norms ($\beta = 0.71$, $p < 0.001$). Hypothesis 3 stated that control beliefs would predict perceived behavioral control. This hypothesis was supported, with Control Beliefs significantly predicting Perceived Behavioral Control ($\beta = 0.80$, $p < 0.001$).

Hypothesis 4, 5,6 stated that attitudes, subjective norms and perceived behavioral control would predict intentions to learn GAI tools for design. All three hypotheses were supported, with attitudes significantly predicting intentions ($\beta = 0.17$, $p = 0.021$), with subjective norms significantly predicting intentions ($\beta = 0.58$, $p < 0.001$) and perceived behavioral control significantly predicting Intentions ($\beta = 0.31$, $p = 0.009$).

Finally, hypothesis 7 stated Awareness of automation will explain additional variance beyond the TPB variables. This hypothesis was not supported, as STARA did not significantly predict Intentions ($\beta = -0.08$, $p = 0.218$).

However, even though path coefficients were mostly supportive of the proposed model, fit indices showed somewhat poor model-data fit, χ^2 (76.248, $df = 15$, $p < .001$), CFI = .833, RMSEA [90% CI] = .210 [.165, .258], SRMR = .156, contrary to expectations. We investigated whether the poor fit could be driven by the inclusion of STARA by re-running the path analysis without the STARA variable. When we did this, fit did improve but was still below conventionally accepted cut-offs, χ^2 (71.036, $df = 12$, $p < .001$), CFI = .809, RMSEA [90% CI] = .203 [.165, .244], SRMR = .176. Path coefficients for this second analysis are shown in Figure 3.

In summary, the model was mostly supported as all path coefficients were significant except the automation awareness coefficient. Despite the significance of these paths, the overall model fit indices indicated a poor fit, suggesting that the model does not fully capture the relationships in the data. This indicates a need for model revision or the inclusion of additional variables or paths to improve the model fit.

Discussion

Generative AI (GAI) can now produce high-quality artworks quickly and indistinguishably from human creations. Despite these benefits this shift has raised concerns about job security and predictions of automation. Out of the various responses to job insecurity, proactive coping stands out as being most beneficial and enhances employability by learning new skills (Lee et al., 2018) such as using GAI tools for augmented creativity. Thus, it becomes essential to identify the antecedents of proactive coping and facilitate human-AI collaboration, ultimately aiding in theory building and creating interventions to support artists in the automation era.

Using an augmented version of the TPB model to analyze the survey results, we identified several predictors of designers' intentions to learn GAI tools. As hypothesized, the factors included behavioral beliefs, normative beliefs, control beliefs, attitudes towards learning GAI tools, subjective norms, and perceived behavioral control. These factors significantly predicted designers' intentions. However, the hypothesis that automation awareness would explain additional variance beyond the TPB variables was not supported.

Theoretical and Practical Contributions

Our investigation makes three substantial contributions to the theoretical and practical side of understanding proactive coping and technology adoption. First, little was known about graphic designer’s decision-making processes to learn GAI for art and design work. While there has been some exploration of technology adoption in general (Salleh & Laxman, 2015; Hou et al., 2022; Teo & Tan, 2012), there is a paucity of studies focusing on the creative industries, particularly among graphic designers. To the best of our knowledge, this study is the first to apply the Theory of Planned Behavior (TPB) to examine the factors influencing intention formation regarding technology adoption among creatives. By employing TPB, this research provides a structured framework to understand the mechanisms behind graphic designers' adoption of GAI, thereby filling a crucial gap in the existing literature.

Second, this study significantly contributes to the proactive coping literature by providing a comprehensive examination of a specific proactive coping behavior—learning new skills—which has been relatively underexplored in previous research. By identifying, testing, and supporting a focused theory on this behavior, the study answers one of the calls listed in the work of Shoss (2017) on pursuing educational opportunities to enhance job prospects and builds on the work of Innocenti & Golin (2022), who initially analyzed the relationship between perceived automation risks and intentions to gain new skill. Our analysis elucidates the motivations behind why individuals might engage in skill acquisition, however contrary to previous assumptions, we could not find impact of automation awareness on learning intentions (Aspinwall and Taylor; 1997, Innocenti & Golin; 2022). This unexpected result suggests that recognizing the potential threats posed by automation may not necessarily drive proactive behavior in terms of acquiring new skills related to GAI.

Third, our model can be used as the basis for interventions. Given the strong support for the TPB’s application to graphic designers' intention to learn GAI provided by the current study, it seems feasible that desirable changes in graphic designers' attitudes, subjective norms, and perceptions of control might lead to corresponding changes in their intentions and behavior. Specifically, the results of the present study suggest that GAI learning interventions may be most successful if they focus on the subjective norms component of the model, given this component was the most important predictor of intentions, as indicated by the size of the path coefficient in the path analysis. Additionally and importantly, subjective norms are possibly amenable to interventions, making them a valuable target for designing effective strategies to promote GAI learning. Thus, if learning of GAI is endorsed by design professionals, managers, clients, and the graphic design field at large, this could create a positive social environment that encourages this behavior and alleviate suspicions around GAI usage. Other people have used the TPB to inform interventions such as public health campaigns and educational programs, demonstrating its versatility and effectiveness in various contexts (Simpson et al., 2022; Jeihooni et al., 2022; Angeli et al., 2022; Pakyar et al., 2021). Similarly, an intervention for graphic designers might include workshops and seminars led by respected industry professionals, mentorship programs that connect experienced designers with novices, and promotional campaigns highlighting the benefits and endorsements of GAI learning from key figures in the design community.

Limitations

The current study has a number of limitations. First, the analysis carried out is based on a cross-sectional design. Hence it is not possible to draw inferences regarding causal relations among the variables. These results should be interpreted as associations, despite the causal predictions being grounded in theoretical logic and prior TPB findings. Future longitudinal research is needed to confirm the causal ordering suggested by these results.

Second, a large number of participants failed attention checks, raising concerns about their motivation. This is a concern because it might indicate that participants were not fully engaged, potentially affecting the reliability of the data. To mitigate this issue, we incorporated incentives and placed the main variables at the beginning of our survey to boost participant motivation. However, future research should attempt to replicate and expand the current results.

Third, the scales used in the study were created specifically for this study and were not previously validated. This could potentially affect the validity of the study's findings. It should be stated that we followed Ajzen’s guidelines (2019) in constructing the survey, which have been utilized in many previous researches (Hamilton et al., 2024; La Barbera & Ajzen, 2020). Additionally, the reliability coefficient for the scales yielded acceptable reliability coefficients, indicating a reasonable level of consistency in the measurements. Nonetheless, future studies should continue the validation efforts that were started in this study.

Fourth, the study focused exclusively on graphic designers, which limits the generalization of findings to other creative professionals. This limitation is a concern because creatives are a heterogeneous group, and differences among various types of creatives were not investigated. Different groups may have different decision-making processes; for example, graphic designers' decision-making processes may not align with those of musicians, who have been found to be autonomously motivated in the context of job insecurity (Alfarone & Merlone, 2022). To minimize this concern, future research should cross-validate the results of this study in different creative professions. It is important to acknowledge that this limitation restricts the generalizability of the findings, and future research should investigate the formation of intentions regarding learning how to use GAI across various types of creative work.

For practical reasons, this study focused specifically on graphic designers' intention to learn using GAI, rather than their behavior. However, this decision puts some limits on the interpretation of our results. First, intention is the principal but not the sole determinant of the adoption of subsequent behavior (Fishbein & Ajzen, 2011). Therefore, while studying intentions provides valuable insights into the motivational aspects of learning GAI, it limits our ability to make concrete predictions about actual learning behaviors. Future studies should consider investigating actual behavior.

Finally, the path analysis model demonstrated a poor fit to the data. Several factors may have contributed to the poor model fit. These include potential measurement error, sample size limitations, and the complexity of the relationships among variables that may not be fully captured by the specified model. For instance, additional variables such as emotional factors and actual behavior that have been previously included in TPB frameworks might need to be included (Kim et al., 2013). Due to the poor model fit, the findings from this path analysis should be interpreted with caution. The relationships identified may not accurately reflect the underlying processes in the population. Future research should consider using larger sample sizes, refining the measurement instruments, and exploring alternative model specifications to improve model fit.

Conclusion

In this study, we aimed to investigate a specific proactive coping behavior - learning new skills – with a focus on the population of graphic designers. Based on our literature review, we concluded that the TPB slightly modified might be a valid model of GAI adoption among this group. Consistent with our expectations, attitudes, subjective norms and perceived behavioral control were significant predictors of intentions. However, we did not find support for automation awareness as a fourth predictor. The next step in this line of research is to confirm the findings here, and if confirmed, investigate if intentions lead to actual behavior in this context. After that, researchers should examine the effectiveness of interventions based on these predictors with social norms being a possible intervention target.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2019). TPB questionnaire construction. *Constructing a Theory of Planned Behavior Questionnaire. https://people. umass. edu/aizen/pdf/tpb. measurement. pdf*

Ajzen, I., & Kruglanski, A. W. (2019). Reasoned action in the service of goal pursuit. *Psychological review*, *126*(5), 774. https://doi.org/10.1037/rev0000155

Alfarone, I., & Merlone, U. (2022). The show must go on: Pandemic consequences on musicians' job insecurity perception. *Psychology of Music*, *50*(6), 1976-2000. https://doi.org/10.1177/03057356221081553

Angeli, M., Hassandra, M., Krommidas, C., Kolovelonis, A., Bouglas, V., & Theodorakis, Y. (2022). Implementation and evaluation of a school-based educational program targeting healthy Diet and Exercise (DIEX) for Greek high school students. *Sports*, *10*(12), 196. https://doi.org/10.3390/sports10120196

Askew, K., Buckner, J. E., Taing, M. U., Ilie, A., Bauer, J. A., & Coovert, M. D. (2014). Explaining cyberloafing: The role of the theory of planned behavior. *Computers in Human Behavior*, *36*, 510-519. https://doi.org/10.1016/j.chb.2014.04.006

Aspinwall, L. G., & Taylor, S. E. (1997). A stitch in time: self-regulation and proactive coping. *Psychological bulletin*, *121*(3), 417. https://doi.org/10.1037/0033-2909.121.3.417

Bode, C., de Ridder, D. T., & Bensing, J. M. (2006). Preparing for aging: Development, feasibility and preliminary results of an educational program for midlife and older based on proactive coping theory. *Patient education and counseling*, *61*(2), 272-278. https://doi.org/10.1016/j.pec.2005.04.006

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239-257. https://doi.org/10.1017/jmo.2016.55

De Witte, H., Vander Elst, T., & De Cuyper, N. (2015). Job insecurity, health and well-being. In J. Vuori, R. W. B. Blonk, & R. H. Price (Eds.), Sustainable working lives: Managing work transitions and health throughout the life course (pp. 109 –128). Dordrecht, the Netherlands: Springer. http://dx.doi.org/10.1007/978-94-017-9798-6_7

Fishbein, M., & Ajzen, I. (2011). *Predicting and changing behavior: The reasoned action approach*. Psychology press. https://doi.org/10.4324/9780203838020

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of business research*, *69*(8), 3192-3198. https://doi.org/10.1016/j.jbusres.2015.12.008

Goldammer, P., Annen, H., Stöckli, P. L., & Jonas, K. (2020). Careless responding in questionnaire measures: Detection, impact, and remedies. *The Leadership Quarterly*, *31*(4), 101384. https://doi.org/10.1016/j.leaqua.2020.101384

Hamilton, K., Phipps, D. J., Schmidt, P., Bamberg, S., & Ajzen, I. (2024). First test of the theory of reasoned goal pursuit: predicting physical activity. *Psychology & Health*, *39*(1), 24-41. https://doi.org/10.1080/08870446.2022.2026946

Hou, M., Lin, Y., Shen, Y., & Zhou, H. (2022). Explaining pre-service teachers' intentions to use technology-enabled learning: An extended model of the theory of planned behavior. *Frontiers in Psychology*, *13*, 900806. https://doi.org/10.3389/fpsyg.2022.900806

Innocenti, S., & Golin, M. (2022). Human capital investment and perceived automation risks: Evidence from 16 countries. *Journal of Economic Behavior & Organization*, *195*, 27-41. https://doi.org/10.1016/j.jebo.2021.12.027

Kelly, J. (2024, February 20). Goldman Sachs predicts 300 million jobs will be lost or degraded by Artificial Intelligence. *Forbes*. https://www.forbes.com/sites/jackkelly/2023/03/31/goldman-sachs-predicts-300-million-jobs-will-be-lost-or-degraded-by-artificial-intelligence/?sh=6005db6782b4

Kim, Y. J., Njite, D., & Hancer, M. (2013). Anticipated emotion in consumers' intentions to select eco-friendly restaurants: Augmenting the theory of planned behavior. *International journal of hospitality management*, *34*, 255-262. https://doi.org/10.1016/j.ijhm.2013.04.004

Khani Jeihooni, A., Layeghiasl, M., Yari, A., & Rakhshani, T. (2022). The effect of educational intervention based on the theory of planned behavior on improving physical and nutrition status of obese and overweight women. *BMC Women's Health*, *22*(1), 13. https://doi.org/10.1186/s12905-022-01593-5

Kline, R. B. (2015). Principles and practice of structural equation modeling (Vol. 4th edition): The Guilford Press.

Knibbs, K. (2023, September 6). *Why this award-winning piece of Ai Art Can't be copyrighted*. Wired. https://www.wired.com/story/ai-art-copyright-matthew-allen/

Koen, J., & Parker, S. K. (2020). In the eye of the beholder: How proactive coping alters perceptions of insecurity. *Journal of Occupational Health Psychology*, *25*(6), 385. https://doi.org/10.1037/ocp0000198

Koen, J., & van Bezouw, M. J. (2021). Acting proactively to manage job insecurity: How worrying about the future of one's job may obstruct future-focused thinking and behavior. *Frontiers in Psychology*, *12*, 727363. https://doi.org/10.3389/fpsyg.2021.727363

Koh, H. E., Oh, J., & Mackert, M. (2017). Predictors of playing augmented reality mobile games while walking based on the theory of planned behavior: web-based survey. *JMIR mHealth and uHealth*, *5*(12), e8470. https://doi.org/10.2196/mhealth.8470

Kong, H., Yin, Z., Baruch, Y., & Yuan, Y. (2023). The impact of trust in AI on career sustainability: The role of employee–AI collaboration and protean career orientation. *Journal of Vocational Behavior*, *146*, 103928. https://doi.org/10.1016/j.jvb.2023.103928

La Barbera, F., & Ajzen, I. (2020). Understanding support for European integration across generations: A study guided by the theory of planned behavior. *Europe's Journal of Psychology*, *16*(3), 437. https://doi.org/10.5964/ejop.v16i3.1844

Langerak, J. B., Koen, J., & van Hooft, E. A. (2022). How to minimize job insecurity: The role of proactive and reactive coping over time. *Journal of Vocational Behavior*, *136*, 103729. https://doi.org/10.1016/j.jvb.2022.103729

Lee, C., Huang, G. H., & Ashford, S. J. (2018). Job insecurity and the changing workplace: Recent developments and the future trends in job insecurity research. *Annual Review of Organizational Psychology and Organizational Behavior*, *5*, 335-359. https://doi.org/10.1146/annurev-orgpsych-032117-104651

Lingmont, D. N., & Alexiou, A. (2020). The contingent effect of job automating technology awareness on perceived job insecurity: Exploring the moderating role of organizational culture. *Technological Forecasting and Social Change*, *161*, 120302. https://doi.org/10.1016/j.techfore.2020.120302

Morriss-Kay, G. M. (2010). The evolution of human artistic creativity. *Journal of Anatomy*, *216*(2), 158-176. https://doi.org/10.1111/j.1469-7580.2009.01160.x

Mukerjee, J., Montani, F., & Vandenberghe, C. (2021). A dual model of coping with and commitment to organizational change: the role of appraisals and resources. *Journal of Organizational Change Management*, *34*(5), 1144-1161. https://doi.org/10.1108/JOCM-01-2021-0027

Teo, T., & Tan, L. (2012). The theory of planned behavior (TPB) and pre-service teachers' technology acceptance: A validation study using structural equation modeling. *Journal of Technology and Teacher Education*, *20*(1), 89-104. https://www.learntechlib.org/primary/p/36090/

Tigre Moura, F., Castrucci, C., & Hindley, C. (2023). Artificial intelligence creates art? An experimental investigation of value and creativity perceptions. *The Journal of Creative Behavior*, *57*(4), 534-549. https://doi.org/10.1002/jocb.600

Nelson, A. J., & Irwin, J. (2014). "Defining what we do—all over again": Occupational identity, technological change, and the librarian/Internet-search relationship. *Academy of Management Journal*, *57*(3), 892-928. https://doi.org/10.5465/amj.2012.0201

Ouwehand, C. (2005). *Proactive coping and successful aging.* [Unpublished doctoral dissertation]. Utrecht University.

Pakyar, N., Poortaghi, S., Pashaeypoor, S., & Sharifi, F. (2021). Effect of educational program based on theory of planned behavior on osteoporosis preventive behaviors: a randomized clinical trial. *BMC Musculoskeletal Disorders*, *22*, 1-10. https://doi.org/10.1186/s12891-021-04861-x

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*, 1-36.

Salleh, S., & Laxman, K. (2015). Examining the effect of external factors and context-dependent beliefs of teachers in the use of ICT in teaching: Using an elaborated theory of planned behavior. *Journal of Educational Technology Systems*, *43*(3), 289-319. https://doi.org/10.1177/0047239515570578

Samo, A., & Highhouse, S. (2023). Artificial intelligence and art: Identifying the aesthetic judgment factors that distinguish human-and machine-generated artwork. *Psychology of Aesthetics, Creativity, and the Arts*. https://doi.org/10.1037/aca0000570

Shoss, M. K. (2017). Job insecurity: An integrative review and agenda for future research. *Journal of management*, *43*(6), 1911-1939. https://doi.org/10.1177/0149206317691574

Simpson, E. E. A., Davison, J., Doherty, J., Dunwoody, L., McDowell, C., McLaughlin, M., ... & Giles, M. (2022). Employing the theory of planned behaviour to design an e-cigarette education resource for use in secondary schools. *BMC Public Health*, *22*(1), 276. https://doi.org/10.1186/s12889-022-12674-3

Stiglbauer, B., & Batinic, B. (2015). Proactive coping with job insecurity—Beneficial or harmful. *Work Stress*, *29*(3), 264-285. https://doi.org/10.1080/02678373.2015.1074956

Tuan, L. T. (2022). How and when does hospitality employees' core beliefs challenge foster their proactive coping for technostress?: Examining the roles of promotion focus, job insecurity, and technostress. *Journal of Hospitality and Tourism Management*, *52*, 86-99. https://doi.org/10.1016/j.jhtm.2022.05.017

Vinchon, F., Lubart, T., Bartolotta, S., Gironnay, V., Botella, M., Bourgeois-Bougrine, S., ... & Gaggioli, A. (2023). Artificial Intelligence & Creativity: A manifesto for collaboration. *The Journal of Creative Behavior*, *57*(4), 472-484. https://doi.org/10.1002/jocb.597

Wanberg, C. R. (1997). Antecedents and outcomes of coping behaviors among unemployed and re employed individuals. *Journal of Applied psychology*, *82*(5), 731. https://doi.org/0021-9010/97/S3.00

Wang, X., Wong, Y. D., Chen, T., & Yuen, K. F. (2022). An investigation of technology-dependent shopping in the pandemic era: Integrating response efficacy and identity expressiveness into theory of planned behaviour. *Journal of Business Research*, *142*, 1053-1067. https://doi.org/10.1016/j.jbusres.2022.01.042

Ward, M. K., & Meade, A. W. (2023). Dealing with careless responding in survey data: Prevention, identification, and recommended best practices. *Annual Review of Psychology*, *74*, 577-596. https://doi.org/10.1146/annurev-psych-040422-045007

Yuan, K.-H., & Bentler, P. M. (2000). Three likelihood-based methods for mean and covariance structure analysis with nonnormal missing data. *Sociological Methodology, 30*(1), 165–200. https://doi.org/10.1111/0081-1750.00078

Table 1

Means, Standard Deviations, alphas and correlations of Study Variables' Aggregate Scores

Variable	*M*	*SD*	α	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1 Intentions	20.55	5.6	.84	1.0							
2 Attitude	24.99	7.22	.87	.67*	1.0						
3 Subjective Norms	20.34	5.11	.79	.82*	.67*	1.0					
4 PBC	21.71	4.81	.80	.71*	.56*	.66*	1.0				
5 BB	333.66	101.56	.85	.70*	.56*	.72*	.62*	1.0			
6 NB	269.98	105.45	.90	.67*	.62*	.71*	.62*	.57*	1.0		
7 CB	178.76	75.95	.94	.71*	.61*	.71*	.8*	.69*	.73*	1.0	
8 STARA	10.18	3.86	.69	-.07	-.06	-.03	.08	.01	-.02	.06	1.0

Note. PBC = Perceived Behavioral Control, BB = Behavioral Belief, NB = Normative Belief, CB = Control Belief.

*p < .05.

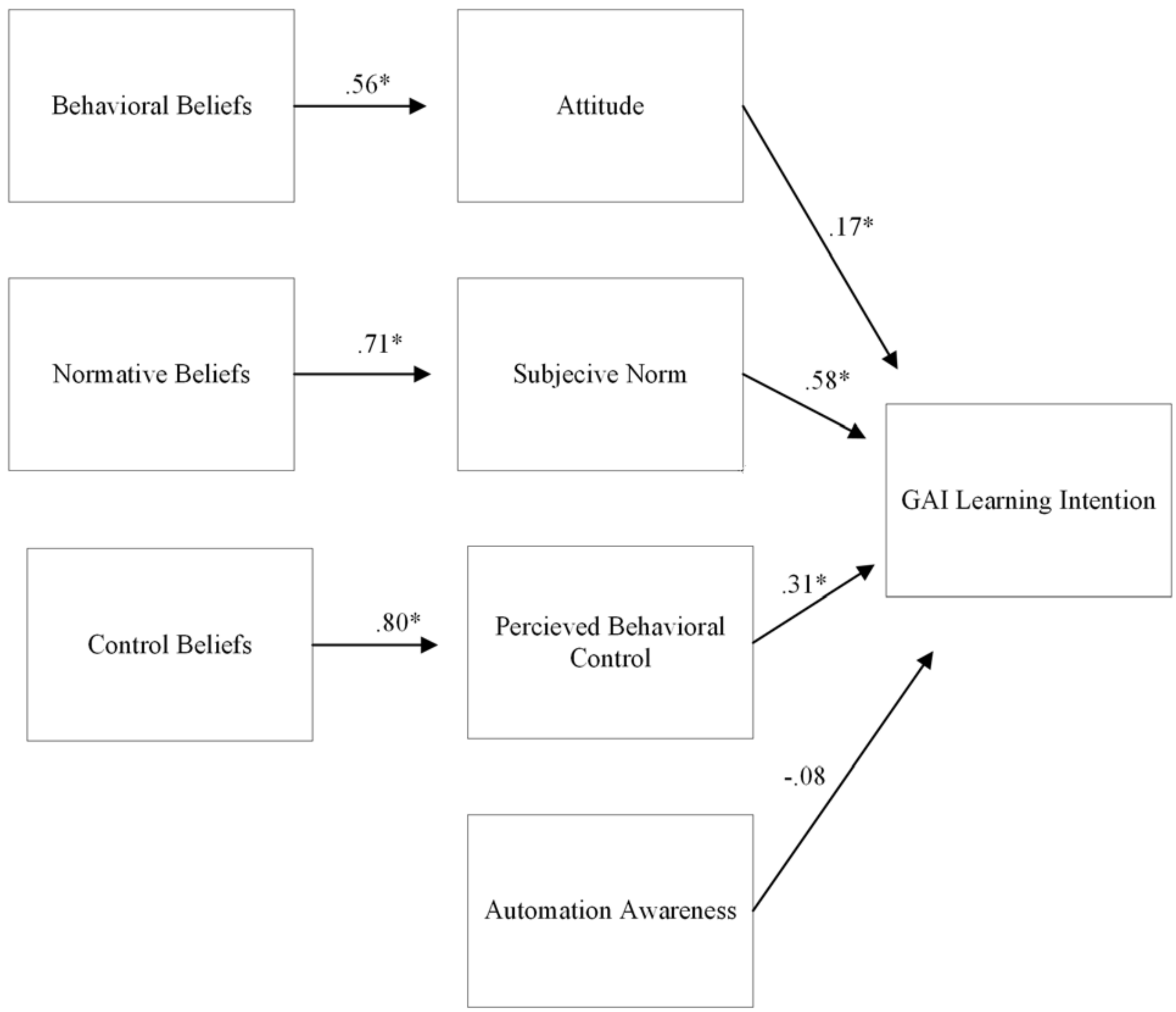
Table 2

Percentages for each response in the STARA scale

Scale	I think my job could be replaced by STARA	I am personally worried that what I do now in my job will be able to be replaced by STARA	I am personally worried about my future in my organization due to STARA replacing employees	I am personally worried about my future in my industry due to STARA replacing employees
Agree	34.5 %	35.3 %	28.7 %	32.2 %
Disagree	15.1 %	21.0 %	12.2 %	13.6 %
Neither Agree nor Disagree	26.1 %	21.8 %	30.4 %	25.4 %
Strongly Agree	14.3 %	16.8 %	16.5 %	17.8 %
Strongly Disagree	10.1 %	5.0 %	12.2 %	11.0 %

Figure 2

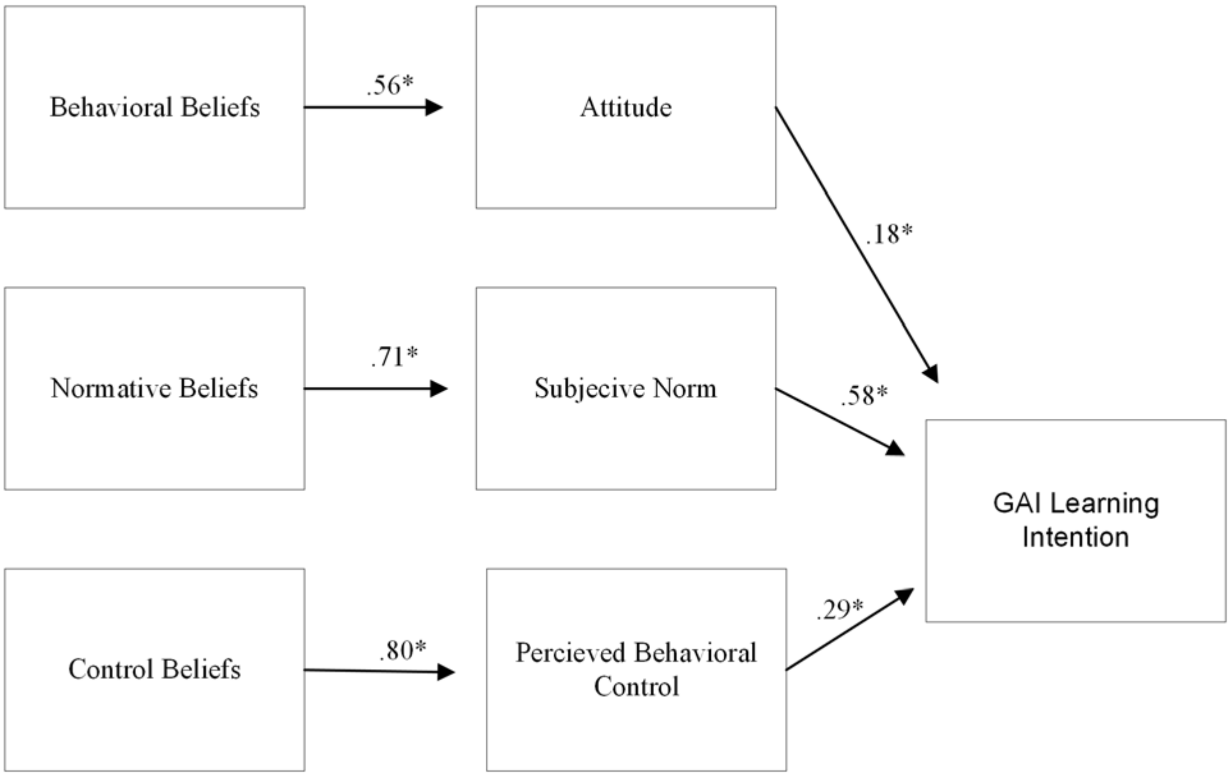
Model 1 including Automation Awareness



Note. *$p < .05$

Figure 3

Model 2 without Automation Awareness



Note. **p* < .05*

Appendix A

Measures used in the study

Construct	Item	Scale
Behavioral Beliefs	If I learn to use Generative AI tools for art and design work, it will - help me quickly generate ideas - help me quickly visualize concepts - take away originality from my work* - expedite repetitive tasks - help in overcoming creative hurdles - serve as a source of inspiration - make my work easier than manual design - save me time - make my work efficient - devalue human creativity* - lead to over reliance on* technology - lead to degradation of design* basics - interfere with my creative* development - steal others work* - replace designers*	[1] Unlikely to [7] Likely
Outcome Evaluation	How valuable are each of the following to you in the near future - Quickly generating ideas - Quickly visualizing concepts - Originality in your work - Expediting repetitive tasks - Overcoming creative hurdles - Sources of inspiration - Making work easier than manual designing - Saving your time - Making work efficient - Human creativity - Over reliance on technology*	[1] Slightly Valuable to [7] Extremely Valuable

	- Design basics - Interference with your creative* development - Stealing people's work* - Replacement of designers*	
Injunctive Normative Belief	How likely do you think that following people would approve of your learning to use generative AI tools? - Design Professionals - Your superior (Feel free to skip this question if you are a freelancer and it is not applicable to you) - Gen Z Peers - Big Corporations - Traditional Designers	[1] Unlikely to [7] Likely
Motivation To Comply	How much do you care whether each of the following people approve or don't approve of what you do? - Design Professionals - Your superior (Feel free to skip this question if you are a freelancer and it is not applicable to you) - Gen Z peers - Big Corporations - Traditional Designers	[1] Not at all - [7] Very much
Descriptive Normative Belief	How likely do you think that the following individuals or groups would learn to use generative AI tools for art and design work? - Non Design professionals - Design Professionals - Students - Graphic Designers in small businesses - Inexperienced Designers - Traditional Designers	[1] Unlikely to [7] Likely
Motivation To Comply	How important are each of these people to you? - Non Design professionals - Design Professionals - Students - Graphic Designers in small	[1] Not at all - [7] Very much

	businesses - Inexperienced Designers - Traditional Designers	
Control Factors	Do you expect to have the following in the near future? - Access to reliable generative AI tools - Tutorials - Access to user friendly tools - Availability of courses - Access to Educators - Availability of budget for learning	[1] Unlikely to [7] Likely
Power of Control Factors	Having the following would enable me to learn using generative AI tools for design work: - Reliable generative AI tools - Tutorials - User friendly tools - Availability of courses - Educators - Budget for learning	[1] Unlikely to [7] Likely
Attitude	For me learning how to use generative AI for art and design work in the near future would be	[1] Unpleasant - [7] Pleasant [1] Bad - [7] Good [1] Worthless - [7] Valuable [1] Harmful - [7] Beneficial [1] Boring - [7] Interesting
Subjective Norm	Most people who are important to me approve of my learning how to use generative AI for art and design work in the near future. Most People whose opinions I value think that I should try to learn how to use generative AI tools for art and design work in the near future. Most people like me will learn how to use generative AI tools for art and design in the near future	[1] Disagree - [7] Agree [1] Disagree - [7] Agree

	Most people I know will make an effort to learn how to use generative AI for art and design work in the near future	[1] Disagree - [7] Agree
		[1] Disagree - [7] Agree
Perceived Behavioral Control	I am confident that I can learn how to use generative AI for art and design work in the near future	[1] Disagree - [7] Agree
	My learning how to use generative AI for art and design in the near future is up to me	[1] Disagree - [7] Agree
	It would be possible for me to learn how to use generative AI for art and design work in the near future.	[1] Disagree - [7] Agree
	I have complete control over whether I learn how to use generative AI for art and design work in the near future	[1] Disagree - [7] Agree
Intentions	I intend to learn how to use generative AI for art and design work in the near future	[1] Disagree - [7] Agree
	I expect to learn how to use generative AI for art and design work in the near future	[1] Disagree - [7] Agree
	It is likely that I will learn how to use generative AI for art and design work in the near future	[1] Disagree - [7] Agree
	I plan to learn how to use generative AI for art and design work in the near future	[1] Disagree - [7] Agree
STARA	I think my job could be replaced by STARA	[1] Strongly Disagree - [7] Strongly Agree
	I am personally worried that what I do now in my job will be able to be replaced by STARA	[1] Strongly Disagree - [7] Strongly Agree
	I am personally worried about my future in my organization due to STARA replacing employees (Feel free to skip this question if you are a freelancer and it is not applicable to you)	[1] Strongly Disagree - [7] Strongly Agree
	I am personally worried about my future in my industry due to STARA replacing employees	[1] Strongly Disagree - [7] Strongly Agree

Note. *Items reverse coded