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Adopting AI-Enabled Technology: Taking the Bad with the Good

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Recommended Citation

Dagliyan, George; Granados, Nelson F.; and Russell, Cristel A., "Adopting AI-Enabled Technology: Taking the Bad with the Good" (2022). *AMCIS 2022 Proceedings*. 16.
https://aisel.aisnet.org/amcis2022/sig_adit/sig_adit/16

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Adopting AI-Enabled Technology: Taking the Bad with the Good

Completed Research Full Paper

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Abstract

From autonomous vehicles to smart home assistants and telemedicine, artificial intelligence (AI) enabled technologies are increasingly available in the market. Consumers are saddled between the benefits and the risks of these new technologies, yet research has seldom accounted for both facilitators and inhibitors of AI-enabled technology adoption. We introduce a theoretical model that includes both facilitators and inhibitors of AI-enabled technologies, which we test using structural equation modeling with a cross sectional survey of U.S. consumers across three AI categories: autonomous vehicles for robotic AI, smart home assistants for virtual AI, and telemedicine for embedded AI. We also include in the model the role of brand trust. We find that perceived uncertainty, loss of control, and privacy risk inhibit intention to use AI-enabled technologies by reducing perceptions of convenience, customization, and efficiency, so facilitators mediate the relationship between inhibitors and intention to use. We also find that brand trust contributes to intention to use by positively affecting facilitators and negatively affecting inhibitors. Finally, we ran the classic Technology Acceptance Model and found that our proposed model is a better fit to predict intention to use AI-enabled technologies.

Keywords

Artificial intelligence, technology design, technology adoption, brand trust

Introduction

By augmenting the tasks performed by consumers, artificial intelligence (AI) can transform their experiences (Russel and Norvig 2013). Consumers can benefit from the convenient, low-cost, reliable, and personalized services that AI-enabled technology offers (Huang and Rust 2020). However, consumers may be concerned about issues related to safety (Zmud et al. 2016), reliability (Foehr and Germelmann 2020), and loss of control (Del Bucchia et al. 2021; Howard and Dai 2014). Surprisingly, prior research has prioritized facilitators of technology adoption, with limited research accounting for the inhibitors.

Understanding the factors that influence consumers' adoption of novel technologies is critical to develop and market new products and services (Claudy et al. 2015). The technology adoption literature has primarily applied traditional behavioral models, including the technology acceptance model (TAM: Davis 1989), and its extension, the unified theory of acceptance and use of technology (UTAUT: Venkatesh et al. 2003). Despite their popularity across contexts, these frameworks leave out critical factors that may inhibit the adoption of novel technologies, and to date, few models include these inhibiting factors (Claudy et al. 2015; Janis and Mann 1977; Westaby et al. 2010).

In this study we investigate consumer adoption across three AI categories: *virtual*, *robotic*, and *embedded* AI (Glikson and Woolley 2020). Virtual AI refers to AI-enabled virtual agents with a distinct identity but no physical presence, such as smart home assistants (SHAs) (e.g., Alexa, Siri). Robotic AI refers to physically present AI-enabled technology, and for this category we study autonomous vehicles (AVs). AVs have the potential to make radical changes in accident fatality, traffic congestion, and mobility. Finally, embedded

AI is invisible AI that has no physical presence or distinguished identity (Glikson and Woolley 2020), and for this category we study telemedicine (TM). AI can revolutionize the healthcare industry with more accurate and less costly diagnoses and treatments made by doctors (Liu et al, 2019).

Notwithstanding the differences between virtual, robotic, and embedded AI categories in terms of their level of machine intelligence, capabilities, complexities, and diffusion stage, their adoption is affected by facilitating and inhibiting factors. Like many technologies, consumers harbor mixed feelings between the benefits of empowerment and the vulnerability that AI conceals (Del Bucchia et al. 2021).

This research also accounts for branding that signals the presence of AI-enabled applications (e.g., Amazon Alexa's smart home assistants, Tesla's AVs), recognizing that trust in a brand affects consumers' perceptions of the technology and therefore the likelihood of adoption and use. This study incorporates the role of brand trust and its different facets across the three AI categories.

Literature Review

Studies in the technology adoption domain have primarily applied traditional behavioral models, including the TAM (Davis 1989) and the UTAUT (Venkatesh et al. 2003). Despite their popularity across many technology contexts, these frameworks have left out inhibiting factors for the adoption of novel technologies (Claudy et al. 2015; Janis and Mann 1977; Westaby et al. 2010). A growing number of researchers have called for incorporating factors that may prevent the adoption of innovations (Antioco and Kleijen 2010; Garcia et al. 2007; Ram and Sheth 1981) and for developing dual-factor models that can account for both inhibitors and enablers of adoption (Balakrishnan et al. 2021). In this section, we briefly review both facilitating and inhibiting factors in the literature of technology adoption to extract the factors most relevant to the adoption of novel technologies in particular.

Technology Adoption and Acceptance

Dillon and Morris (1996) define acceptance of technology as the consumer's willingness to use technology for the activities that it is designed to support. Although seemingly simple, understanding why individuals accept or reject new technologies is a daunting challenge. At present, the technology adoption literature focuses mainly on the facilitators of adoption. The TAM (Davis 1989) is perhaps the most tested theoretical framework in technology adoption. The TAM focuses on the factors that drive acceptance of new technologies (Venkatesh and Davis 2000) and postulates that the two main drivers of acceptance are perceived usefulness (PU) and perceived ease of use (PEOU). Other factors that drive adoption are product attributes like relative advantage, compatibility, and trialability (Claudy et al. 2015).

The TAM has been applied in many domains in the organizational context and in some consumer contexts, including social networking, smartphones, and online learning. TAM has also been used in the AI domain (Sundar et al. 2016; Wu et al. 2019; Zhang et al. 2019). The UTAUT was used to investigate willingness or intent to use smart technologies (Deb et al. 2017; Fritz et al. 2016; Rahman et al. 2017). However, despite its long history, TAM and its constructs may not be as relevant to AI-enabled products and services that are easy to learn and use (Gursoy et al. 2019) and where the AI component, which can be relatively complex for consumers, is more of a black box that works behind the scenes.

Facilitators of Novel Technology Adoption

Based on an extensive review and synthesis of the extant literature on novel technologies, we identified six facilitating and inhibiting factors that could influence the adoption of AI-enabled technologies, as follows:

Convenience. The construct relates to the amount of time and effort required to accomplish a task (Collier and Kimes 2013). It also represents the cognitive, emotional, and physical burdens of using novel technologies (Chang et al. 2012). For example, De Kerviler et al. (2016) found that perceived convenience is one of the critical factors in the use of proximity mobile payments.

Customization. Mass customization has been the central focus of organizations and marketers for decades (Davis, 1987; Pine, 1993). AI-enabled technologies can ease the trade-off between cost and customization with machine learning algorithms that customize products and services at low cost.

Efficiency. Consumer perceptions of efficiency are essential for AI-enabled technology. Researchers often measure efficiency under different latent variables. For example, in the technology readiness model, Parasuraman (2000) measures efficiency under the optimism construct (e.g., technology makes you more efficient in your occupation), and Gursoy et al. (2019) associate perceptions of efficiency with performance expectancy (e.g., AI devices are more accurate, with less human error).

Inhibitors of Novel Technology Adoption

Uncertainty. Uncertainty about the technology's outcome may negatively influence adoption (Lee and Turban 2001). Uncertainty avoidance influences risk aversion and increases reliance on risk-reducing strategies (Hwang 2009). In particular, for AI-enabled technology, the algorithmic black box is complex and ambiguous for the lay person, which increases uncertainty about the outcome.

Privacy Risk. Studies have shown that perceived privacy risk affects intention to use technology (Cazier et al. 2007; Kyriakidis et al. 2015; Li et al. 2016; Schoettle and Sivak 2014). AI can provide consumers increased customization, convenience, and efficiency, but often at the expense of sharing personal and sensitive data, including medical history, location, likes, behaviors, friends, and favorite brands.

Loss of Control. Research suggests that consumers like to be in control (Burger and Cooper 1979). This is especially true when it comes to AI-enabled technologies such as home care robots (Ziefle and Valdez 2017) or AVs (Buckley et al. 2018). Yet, relinquishing some control is an essential aspect of AI-enabled products and services because many actions, recommendations, and decisions are left to the machine. At one extreme, AI-enabled technologies take full control, for example, in the context of AVs.

The Role of Brand Trust

Prior research suggests that trust plays a role in the adoption of technology in general (Gefen 2004) and specifically when it comes to automation (Carter and Bélanger 2005; Gefen and Straub 2003; Lee and Moray 1992, 1994; Lee and See 2004; Parasuraman et al. 2008; Pavlou 2003). Trust is an important factor in the adoption of AI technology (Kaur and Rampersad 2018), including for AVs (Choi and Ji 2015; Zhang et al. 2019). A review of 150 empirical studies underscored the important role of trust in the use AI-enabled technology (Glikson and Woolley 2020). The uncertainty inherent in the use of AI-enabled technology may inhibit the adoption, while trust can mitigate such constraints (Brown et al. 2004).

The exact role of trust in the technology acceptance literature is subject to some debate (Wu et al. 2011). Within the TAM model, some researchers position trust in the technology as an antecedent of PU and PEOU (Choi & Ji 2015), others as their outcome (Kaur & Rampersad, 2018; Zhang et al. 2019).

If direct contact between consumers and the company is not possible, consumers develop a relationship with the brand (Delgado-Ballester 2004; Sheth and Parvatiyar 1995). Trust in a brand allows consumers to believe that the brand is reliable and will deliver the promised value, also known as brand reliability (Delgado-Ballester, 2004). Brand trust also increases perception of brand benevolence, defined as the brand's decency, goodwill, and good intentions. These facets of brand trust can develop from consumers' experience with the brand and prior to any interaction with novel technology (Foehr & Germelmann, 2020). As such, we theorize that brand trust is an antecedent of inhibitors and facilitators of technology adoption.

Conceptual Framework and Hypotheses

Figure 1 depicts the conceptual framework and hypotheses. Based on existing theoretical arguments summarized in the above literature review, the proposed empirical framework includes facilitators and inhibitors as separate constructs and brand trust as an antecedent of these constructs, all of which are directly or indirectly related to consumers' intention to use AI-enabled technologies. These proposed relationships are reflected in the following hypotheses:

Hypothesis 1. Perceptions of facilitating factors are positively related to intention to use AI-enabled technology.

Hypothesis 2. Perceptions of inhibiting factors are negatively related to intention to use AI-enabled technology.

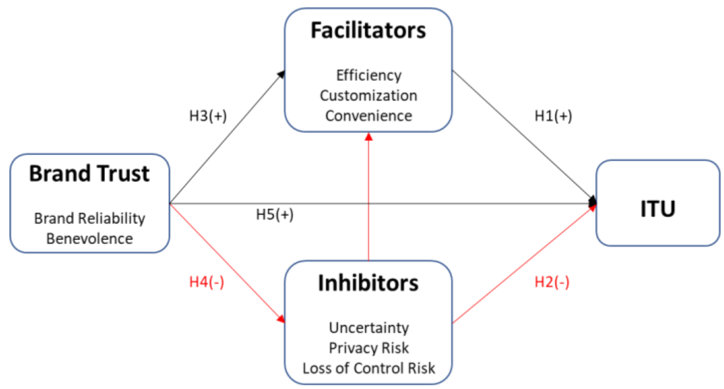

Figure 1. Conceptual Framework and Hypotheses

We hypothesize that brand trust is an antecedent of facilitators, inhibitors, and the intention to use AI-enabled technology, based on the rationale above on the role of brand trust:

Hypothesis 3. Brand trust is positively related with facilitators.

Hypothesis 4. Brand trust is negatively related with inhibitors.

Hypothesis 5. Brand trust is positively related with intention to use AI-enabled technology.

Method Overview

We conducted three studies focusing on the perceptions of AVs (Robotic AI, N = 1,237), SHAs (Virtual AI, N = 894), and TM (Embedded AI, N = 903). The sample size for each study was determined based on the number of parameters being estimated, using Kline's (2015) recommendation of a N:q ratio of 10:1 as the minimum. The number of parameters in the model was (8*9)/2 = 36 so the minimum sample size is 360 observations. We set the sample size to be substantially higher than the minimum of 360 cases.

Survey data were collected from an online consumer panel that was representative of the U.S. population. We used proportionate stratified sampling (Ruel et al. 2015) to ensure that gender, geography, and race distribution were representative of the population. All participants who completed the survey matched the required age range (19+), the targeted regional representation (21% Midwest, 18% Northeast, 37% South, 23% West), even gender split (50% females), and racial diversity (38% non-White).

Participants were screened on whether they had ever used the AI technology, and only non-users (potential adopters) were retained for analysis. Survey quality was controlled by adding two attention check items to the instrument at the 25% and 75% completion points and by imposing a time limit. Finally, the order of items within each measure was randomized to reduce the risk of common method bias.

Measures

Measures for all constructs were adapted from prior literature. All measures were pretested, and their reliability was checked in a pilot phase. All items were measured on seven-point Likert scales ranging from (1) strongly agree to (7) strongly disagree. The questionnaires included four sections. The first section began with a video introduction of the AI technology, and respondents were asked if they had heard of the technology or used it prior to the study. In the second section, respondents completed the survey for each construct. The third section focused on brand trust operationalized as reliability and benevolence (Delgado-Ballester, 2004), where participants could select from a preset list of 10 brands or they could enter another brand. The final section covered demographics (i.e., age, gender, education, marital status, and income).

Results

Analyses were conducted using SPSS-27 and STATA-17. The dataset was screened for unusual patterns, duplicates, and missing values. The overall fit indices demonstrated good fit across all three studies. As recommended by Kline (2015), we used the ratio of chi-square value to the degree of freedom, comparative fit index (CFI), standard root mean square residual (SRMR), and root mean square error of approximation (RMSEA) as goodness of fit indices. We considered a model a good fit when $\frac{\chi^2}{df} < 2$, CFI > 0.95, SRMR < 0.08, and RMSEA < 0.06 (Hu and Bentler 1999; Kline 2015). Although the chi-square test of the models was statistically significant, normally an indication of misfit, this indicator is sensitive to large sample size (Kline 2015). All CFI values were greater than 0.95, SRMR values were lower than 0.08, and RMSEA values were equal to or lower than 0.6. All factor loadings were statistically significant, ranging from 0.69 to 0.98, above the cutoff value of 0.5. Note that, in line with Chin (1998) and Jarvis et al. (2003), we treated facilitators and inhibitors as reflective constructs. This was also justified because the model achieved configural invariance, that is, the factor structure did not change across the studies.

As seen in Table 1, the measures in all three studies achieved high reliability and convergent validity, with assessments of composite reliabilities (CR) and AVE exceeding the recommended level of 0.5 for AVE (Hair et al. 2006) and 0.7 for CR (Bagozzi and Yi 2012). We followed the Fornell and Larcker (1981) criterion to assess discriminant validity. The square root of AVE for each construct was greater than any bivariate correlations involving the constructs in the model (Fornell and Larcker 1981). The maximum shared variances (MSV) and average shared variances (ASV) were also smaller than the AVE for each construct. The results provide evidence that the constructs have a good overall convergent and discriminant validity, and the measurement model shows satisfactory reliability and validity.

Study 1: Automated Vehicles (N = 1237)								
Construct	CR	AVE	MSV	ASV	FAC	INH	BT	ITU
Facilitators (FAC)	0.962	0.893	0.804	0.384	**0.945**			
Inhibitors (INH)	0.860	0.674	0.318	0.243	(0.564)**	**0.821**		
Brand Trust (BT)	0.941	0.888	0.405	0.227	0.637**	(0.363)**	**0.942**	
Intention to Use (ITU)	0.965	0.903	0.804	0.368	0.897**	(0.547)**	0.607**	**0.95**
Study 2: Smart Home Assistance (N = 894)								
Facilitators (FAC)	0.969	0.912	0.802	0.422	**0.955**			
Inhibitors (INH)	0.874	0.700	0.355	0.282	(0.532)***	**0.836**		
Brand Trust (BT)	0.915	0.844	0.598	0.369	0.773***	(0.596)***	**0.919**	
Intention to Use (ITU)	0.969	0.912	0.895	0.397	0.895***	(0.518)***	0.721***	**0.955**
Study 3: Telemedicine (N = 903)								
Facilitators (FAC)	0.961	0.891	0.799	0.327	**0.944**			
Inhibitors (INH)	0.876	0.703	0.315	0.211	(0.494)**	**0.838**		
Brand Trust (BT)	0.929	0.868	0.266	0.141	0.516**	(0.270)**	**0.932**	
Intention to Use (ITU)	0.954	0.874	0.799	0.310	0.894**	(0.460)**	0.472**	**0.935**

Note. CR: Composite Reliability; AVE: Average Variance Extracted; MSV: Maximum Shared Variances; ASV: Average Shared Variances. Square root of the AVE is presented in bold on the diagonal. *p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 1. Correlations and Discriminant Validity by Study

Table 2 presents the summary of our hypothesis testing with path coefficients for H1, H2, H3, H4, and H5. The results supported all hypothesized relationships. The relationship between brand trust and intentions to use was almost fully mediated by facilitators (brand trust is related to higher perceptions of facilitating factors) and inhibitors (brand trust is related to lower perceptions of inhibiting factors). In addition, the analyses revealed a direct, negative relationship between inhibitors and facilitators. The results provide a novel insight into the role of inhibiting factors in the adoption of novel technology and of AI-enabled technologies in particular. We discuss these insights further in the Discussion section.

Hypotheses	Study 1 (AV)	Study 2 (SHA)	Study 3 (TM)
H1: FAC → ITU	0.793 ***	0.794 ***	0.882 ***
H2: INH → ITU	(0.168)**	(0.097)**	(0.105)**
INH → FAC	(0.523)***	(0.257)***	(0.696)***
H3: BT → FAC	0.433 ***	0.626 ***	0.339 ***
H4: BT → INH	(0.385)***	(0.582)***	(0.254)***
H5: BT → ITU	0.040	0.050	0.012

Note. Standardized Path Coefficients. *p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 2. Results of Hypothesis Testing

Competing Model Findings

We collected data to test and compare our new theoretical model with the TAM. The overall goodness of fit indices for the TAM model was acceptable for Study 1 and Study 3, with an RMSEA of 0.10, above the recommended value of 0.6. The overall goodness of fit indices for the TAM model was not acceptable for Study 2 (smart home assistance).

All coefficients were statistically significant for PU, PEOU, and ITU for each study, but the relationship between PEOU and ITU had a different sign in Study 2 (SHA) compared to Studies 1 and 2. TAM did not achieve configural invariance, which means that groups did not have the same factor loading configuration. This configural variance indicates a major limitation of TAM to estimate novel technologies because it implies that the PEOU construct is not measuring the same thing across different types of AI technologies.

Effects	Study 1 (AV) *N* = 1237	Study 2 (SHA) *N* = 903	Study 3 (TM) *N* = 894
PU → ITU	0.739***	1.180 ***	0.678***
PEOU → ITU	0.176***	(0.291)***	0.195***
PEOU → PU	0.859***	0.860 ***	0.784***

Note. *p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed)

Table 3. Technology Acceptance Model Hypothesis Testing (TAM)

Discussion

Summary of Key Findings

The findings reveal that convenience, customization, and efficiency are facilitators in the adoption of AI-enabled technology. Together they almost fully mediate the relationship between inhibitors and intention to use, and the relationship between brand trust and intention to use. Interestingly, we find that facilitators and inhibitors coexist but, surprisingly, inhibitors mostly affect facilitators directly and intention to use indirectly through the facilitators. This makes the decision for the consumer non-trivial, since there are trade-offs to be made between the risks inherent in the inhibitors and the benefits inherent in the facilitators. For example, customization of recommendations comes at the risk of losing privacy. These trade-offs also have implications for the design and customization options provided by AI-enabled solutions.

This study also highlights the critical role of trust in consumers' adoption of AI-enabled technologies. We find that brand trust positively affects perceptions of facilitators and negatively affects perceptions of inhibitors. Brand trust not only enhances perceptions of convenience, customization, and efficiency, but it also reduces perceptions of uncertainty, risk of privacy, and loss of control risk.

Theoretical Implications

By addressing the interplay of three key antecedents (i.e., facilitators, inhibitors, brand trust) of technology adoption, the tested model in this study provides new theoretical insights into the adoption of AI-enabled technologies. The model addresses the limitations of existing technology acceptance models that focus on facilitating factors (Davis 1989; Kleijnen et al. 2009; Venkatesh et al. 2003). We find that facilitating and inhibiting factors coexist to influence the adoption of AI-enabled technologies.

In line with the growing body of consumer research on brands as relationship partners (Delgado-Ballester 2004; Fournier 1998), the results show that brand trust is an important antecedent of AI-enabled technology adoption, possibly by reducing perceptions of risk and enhancing perceptions of the benefits including customization. More broadly, the findings suggest that branding can influence the adoption of novel technologies by shaping consumer perceptions.

Finally, the findings reveal that TAM has a poor model fit to explain the adoption of AI-enabled technologies because of the strong correlation between perceived usefulness and perceived ease of use. This lack of fit of the TAM model may become more evident as improvements in ease of use increasingly make technology interfaces more user friendly. While the TAM may continue to be useful for conventional technologies or for corporate software, it may be increasingly limited as a predictor of adoption of novel technologies. AI-enabled applications are increasingly simple and easy to use, based on human-like interfaces (e.g., voice) and intuitive outcomes (e.g., automated driving, enhanced medical diagnosis). This may lead to a ceiling effect in measures of ease of use, whereby it consistently scores very high and therefore skews high, so it does not help explain the variance in intention to use. Nowhere is this issue more evident than for easy-to-use smart home applications, where the TAM model did not have a good model fit, perhaps because voice-activated commands and personalized recommendations make the smart home devices very easy to use.

Practical Implications

This research adds nuance to existing models of adoption of AI-enabled technology that can help developers and marketers identify levers to increase the adoption of these new technologies. The findings are relevant not only in the context of highly intelligent, fully autonomous vehicles, which are still in the development and testing stages but also for other products and services in the market, such as smart home assistance and telemedicine. Novel technologies offer features such as customization, convenience, and efficiency. But so far, research has seldom included inhibiting factors. The high percentage of failure of innovations and of new products can be in part because of consumers' resistance to change (Garcia et al. 2007; Kleijnen et al. 2009; Ram 1987; Ram and Sheth 1989). Therefore, companies, marketers, and other stakeholders must overcome this resistance before adoption begins (Claudy et al. 2015; Laukkanen et al. 2007). This research uncovers three possible sources of resistance for AI-enabled applications: privacy risk, uncertainty, and loss of control risk. More broadly, novel technology companies should develop features that reduce consumers' perceptions of risk.

Another practical implication lies in the role of brand trust. Branding is especially relevant in the highly competitive, fast-growing markets for AI-enabled products and services, so brand trust can play an important role in acquiring and retaining customers. Technology companies will benefit from anchoring their technology offerings on a trustworthy brand, whether through a parent brand or a brand extension.

Limitations and Future Research

Notwithstanding these novel findings, there are a few limitations. First, the online data collection may have skewed participation toward tech-savvy consumers. Also, participants responded to hypothetical AV scenarios as fully automated vehicles are not yet available.

Because of its cross-sectional design, the study was limited to observations at one point in time. This limitation prevents observation of change patterns and evolutionary effects across time, which is evident as new AI-enabled applications emerge and as consumers become more familiar with them. Future research could adopt a longitudinal approach to address this limitation.

Conclusions

Advanced and novel technologies such as AI are paving the way for our future. These technologies increasingly impact how consumers shop, commute, interact with each other, take care of their health, run errands, work, and live their lives. Emerging technologies continue offering more and more capabilities to make life easier, and AI-enabled technologies in particular offer convenience, customization, and efficiency. However, with the novelty of these technologies also comes concerns about privacy risk, uncertainty, and loss of control, which are bound to hinder the rate of adoption.

We contribute with a better understanding of the interplay between inhibitors and facilitators of AI-enabled technology adoption, namely that perceptions of uncertainty and risk reduce the perceived benefits, which in turn impacts intention to adopt. Branding can positively influence this interplay by reducing perceptions of risk and positively affecting the perceived benefits including customization. It is evident from the results that consumers often take the good with the bad when considering the adoption of AI-enabled technologies, and perhaps more broadly, of novel technologies in general.

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