Technological Forecasting & Social Change 226 (2026) 124576

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Sustainable last-mile delivery: Understanding perceived benefits and risks of AI-automated delivery drones in France[☆]

Lars Meyer-Waarden[a,b,c], Julien Cloarec[d,*], Stéphane Salgado[a], Vincent Favarin[e]

[a] TSM-Research [UMR 5303 CNRS], Toulouse School of Management, University Toulouse Capitole, Toulouse, France
[b] Chulalongkorn Business School, Chulalongkorn University, Bangkok, Thailand
[c] Lee Shau Kee School of Business & Administration, Hong Kong Metropolitan University, Hong Kong
[d] Université Jean Moulin Lyon 3, iaelyon School of Management, Magellan, Lyon, France
[e] Université Clermont Auvergne, IAE Clermont Auvergne School of Management, CleRMa, Clermont-Ferrand, France

ARTICLE INFO

Keywords:
AI-automated delivery drones
Last-mile delivery
Environmental concerns
Product criticality
Well-being

ABSTRACT

This study investigates the adoption of delivery drones in last-mile logistics by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with constructs related to well-being, perceived technology risk, privacy concerns, and environmental concerns. Drawing on a 2x2x2 experimental design involving 3212 French participants, we examine how physical accidents, cyberattacks, product criticality, and environmental values shape consumers' performance expectancy, social influence, risk perception, and behavioral intentions. The findings show that environmental concerns enhance the positive impact of performance expectancy and social influence on well-being, while unexpectedly reducing the negative effect of privacy concerns. Product criticality significantly weakens the relationship between well-being and adoption intention. This paper contributes theoretically by integrating sustainability and perceived risk theory into UTAUT2, thereby advancing understanding of how consumers evaluate novel autonomous technologies under conditions of uncertainty and ecological awareness.

1. Introduction

The accelerating growth of e-commerce and urbanization has placed increasing pressure on traditional delivery systems. This exacerbates traffic congestion in urban areas and contributes to air pollution (Schwela and Zali, 2020). Consequently, alternative methods for transporting and delivering goods need to be explored. In response, retailers are exploring innovative last-mile logistics solutions, such as AI-automated delivery drones, to meet evolving customer demands while reducing environmental impacts. AI-automated delivery drones promise to alleviate urban congestion, cut emissions, and enhance delivery speed, thereby influencing customer satisfaction and loyalty (Ramadan et al., 2017). An AI-automated drone, technically known as an unmanned aerial vehicle (UAV), is an aircraft that operates without a human pilot on board. Many e-commerce firms and retail giants, including Amazon, Google, and Walmart, are preparing to offer delivery services via AI-automated drones. AI-automated drone delivery could provide a more efficient means of delivering products compared to traditional truck delivery (Goodchild and Toy, 2018) or individual trips to stores (Yoo et al., 2018). Notably, AI-automated drone delivery is also seen as a more sustainable option, potentially reducing the carbon footprint associated with conventional delivery methods, as AI-automated drones consume less energy and can bypass traffic congestion (Mahmoodi et al., 2024). SF Express, a Chinese delivery and logistics company, can dispatch over 500 packages daily via AI-automated drones in cities across southern and eastern China (Ramadan et al., 2017). Domino's Pizza in New Zealand achieved a delivery distance of thirty-two kilometers in less than five minutes using its AI-automated drone delivery service (Reid, 2016). Similarly, major retailers are no longer merely experimenting with AI-automated drone delivery but are actively scaling and operationalizing it across the U.S., signaling the emergence of a structured delivery ecosystem. Amazon, for instance, now integrates AI-automated drone delivery into its standard logistics operations, offering 60-min delivery in select cities with plans for further

☆ This article is part of a special issue entitled: 'Human-Centered Technology' published in Technological Forecasting & Social Change.

* Corresponding author.
E-mail addresses: lars.meyer-waarden@tsm-education.fr (L. Meyer-Waarden), julien.cloarec@univ-lyon3.fr (J. Cloarec), stephane.salgado@tsm-education.fr (S. Salgado), vincent.favarin@uca.fr (V. Favarin).

https://doi.org/10.1016/j.techfore.2026.124576
Received 24 October 2024; Received in revised form 15 January 2026; Accepted 28 January 2026
Available online 3 February 2026

expansion (Amazon, 2025). Walmart is also extending its AI-automated drone services to five additional cities, reinforcing its commitment to fast and flexible retail logistics (Walmart, 2025). Likewise, DoorDash has partnered with Wing, an Alphabet/Google subsidiary, to deploy AI-automated drone delivery in Charlotte, demonstrating how food delivery platforms are integrating this technology at scale (DoorDash, 2025).

The UAV market reached USD 30.2 billion in 2024 and is expected to grow to USD 48.5 billion by 2029 (Markets and Markets, 2024). The expanding market for online shopping and parcel delivery methods for direct-to-consumer delivery, is driving growth in the delivery market (Yoo et al., 2018), with the commercial segment of the market projected to grow at the highest CAGR rate of 28% by 2026. AI-automated delivery drones have the potential to address issues like urban traffic congestion and reduce associated greenhouse gas emissions as well as environmental impact (Stolaroff et al., 2018), and thus offer a sustainable alternative to fuel-powered delivery vehicles to resolve the last-mile delivery problem in mass retail (Goodchild and Toy, 2018). The "last mile" refers to the final and often most complex and costly segment of the delivery process, involving the transportation of goods from a distribution hub to the end customer, particularly challenging in urban areas due to dense infrastructure and high delivery expectations (Koh et al., 2023).

However, despite these advantages, public adoption of AI-automated drone delivery services remains uncertain. Emerging research has begun to explore factors influencing AI-automated drone acceptance. Existing research on AI-automated delivery drones largely focuses on perceived benefits (such as performance or efficiency; Venkatesh and Thong, 2012) and risks (notably privacy concerns), typically examining them as independent predictors of consumer acceptance. However, findings regarding social influence, innovation resistance, and task-technology fit remain mixed, and emotional or symbolic outcomes like well-being are rarely addressed. While some emerging work explores moderating factors like demographics or personality, the field lacks integrated models that consider affective, cognitive, and contextual dimensions in real-world settings.

Yet, critical gaps remain in our understanding of how consumers weigh perceived benefits and risks, particularly when delivery contexts involve sustainability concerns, product criticality (e.g., medical supplies), and emerging safety threats such as cyberattacks. The literature on AI-automated delivery drone adoption often treats perceived benefits and risks in isolation by using technology acceptance models like TAM (Davis, 1989) or UTAUT2 (Venkatesh and Thong, 2012), failing to account for their interaction or contextual moderators such as environmental concerns or product criticality. Emotional outcomes like well-being and trust, though central to transformative consumer research, have been largely overlooked as mediators. Real-world complexities, such as cyberattacks, physical accidents, and critical delivery contexts (e.g., medical vs. retail products), are rarely integrated into existing models. Finally, negative scenarios and their psychological impacts remain underexplored, leading to overly simplistic assessments of consumer technology acceptance. Prior studies isolate these factors, leaving unexplored their potential interactions and joint effects on user well-being and adoption intentions.

This study addresses these gaps by extending the UTAUT2 model (e.g., performance expectancy, social influence) with additional variables such as technology risks, privacy concerns, and well-being. It also examines the moderating role of environmental concern and product criticality. Our contribution thus lies in offering a more holistic view of user acceptance for AI-automated drone delivery technologies, grounded in both utilitarian and affective appraisals. We thus formulate the following research questions: How do perceived benefits (e.g., performance expectancy, social influence) and risks (e.g., technology and privacy concerns) interact to influence consumer well-being and intention to adopt AI-automated delivery drones? How does environmental concerns moderate the effects of benefits and risks on well-being and behavioral intention in the context of AI-automated drone-based last-mile delivery? To what extent does product criticality (e.g., medical vs. retail goods) moderate the relationship between consumer well-being and their intention to adopt AI-automated drone delivery services, especially under conditions of physical or cybersecurity threats?

To answer these questions, we used a 2x2x2 between-subjects experimental design with 3212 respondents from France to explore the influence of product category (grocery retail products vs. medical drugs), the occurrence of physical accidents, and the presence of cyberattacks on participants' perceptions and behavioral intentions regarding AI-automated delivery drones. By doing that our study makes three key contributions to the existing literature on AI-automated delivery drones. First, it shows that environmental concerns not only boost consumer intentions to adopt AI-automated delivery drones but also positively moderate the relationship between performance expectancy, social influence, and well-being (Hwang and Kim, 2019), while revealing a nuanced interaction where higher environmental concerns can unexpectedly mitigate the negative impact of privacy concerns, challenging findings by Khan et al. (2019) and Jiang et al. (2023). Second, our research introduces the concept of product criticality as a significant moderating factor, demonstrating that the positive impact of well-being on the intention to use AI-automated delivery drones diminishes when the product being delivered is of high criticality, such as medical supplies, thereby refining the insights (Hagtvedt and Patrick, 2009; Zaichkowsky, 1985). Third, our study contributes empirical evidence on the effects of physical accidents and cyberattacks, supporting the concerns raised (Luppicini and So, 2016; Ravich, 2017), and aligning with the findings of Martins et al. (2014)and Choe et al. (2021) by showing that these events increase perceived technology risks and decrease performance expectancy, highlighting the importance of addressing safety and security issues to foster consumer trust and adoption of AI-automated delivery drones.

This article is structured as follows: Section 2 reviews the theoretical background and literature review; Section 3 develops the hypotheses; Section 4 outlines the methodology; Section 5 presents the results; and Section 6 discusses theoretical contributions, policy implications, and future research directions.

2. Theoretical background and literature review

2.1. Last-mile AI-automated delivery drones and sustainability

AI-automated delivery drones have emerged as a viable solution to last-mile inefficiencies. Scholars have highlighted their ecological potential due to electric propulsion and route optimization (Chen et al., 2021; Chen et al., 2022; Manfreda et al., 2019; Stolaroff et al., 2018). In large urban areas, where traffic congestion is a persistent issue, AI-automated delivery drones can alleviate this problem by reducing the number of delivery vehicles on the road. In terms of performance, AI-automated drones are highly efficient. This innovation is particularly well-suited for the "last-mile" logistics of small, lightweight items. Thus, AI-automated delivery drones present a promising solution to a range of challenges, offering significant benefits for both the environment and the efficiency of urban logistics.

Yet, their adoption is complicated by public concerns regarding safety, privacy, and system failures (Mathew et al., 2021). Research increasingly acknowledges the psychological and symbolic dimensions of AI-automated drone technology acceptance, positioning it as a test case for future autonomous logistics.

2.2. Literature about the acceptance of last-mile delivery drones

The literature on the adoption of last-mile AI-automated delivery drones explores a variety of psychological, technological, and contextual drivers of consumer acceptance (see Table 1). Most studies rely on established technology acceptance frameworks such as the Technology

Table 1
Literature on factors influencing user acceptance of last-mile AI-automated delivery drones.

Authors	Background	Data and methods	Findings
Khan et al. (2019)	Theory of planned behavior TAM	Survey ($n = 307$) SEM	Privacy concerns negatively impact the intention to use delivery drones.
Hwang and Kim (2019)	Theory of green marketing Technology acceptance	Survey ($n = 427$) SEM	Positive green image enhances attitudes toward delivery drones, which influences their intention to use. Moderated by age and gender.
Kapser and Abdelrahman (2020)	UTAUT2 with Risk	Survey ($n = 509$) SEM	Performance expectancy and risk perception significantly affect behavioral intention.
Leon et al. (2021)	Privacy calculus, TAM	Survey ($n = 617$), PLS-SEM	Perceived usefulness and trust strongly increase intention to adopt drone delivery. Privacy disposition, concern, and risk reduce adoption; legislative protection slightly mitigates privacy risk.
Holzmann et al. (2021)	UTAUT2	Survey ($n = 146$) SEM	Performance expectancy, facilitating conditions, and prior experience drive intention; social influence not significant.
Osakwe et al. (2022)	Risk Perception	Survey ($n = 381$), SEM	Delivery risk perception is a crucial deterrent in last-mile drone adoption.
Jiang et al. (2023)	Resource Matching Service quality	Survey ($n = 255$) SEM	Privacy protection and delivery reliability enhance perceived value and usage intention.
Koh et al. (2023)	TAM, Task–Technology Fit, Privacy Calculus	Survey ($n = 450$), SEM	Perceived usefulness, attitude, and perceived privacy risks directly affect behavioral intention. Ease of use, task/tech characteristics, task-tech fit, and privacy concerns act indirectly. Privacy risk negatively impacts use.
Sham et al. (2023)	Innovation resistance	Survey ($n = 291$) fsQCA, SEM	Value/image/usage barriers lead to switching intentions; mitigated by shopping motivation.
Lim et al. (2024)	Task-technology fit	Survey ($n = 550$) SEM	Hedonic/utilitarian value and trust drive task-tech fit, reuse, and WOM.
Shahzad et al. . (2024)	Behavioral Reasoning Theory, TAM	Survey ($n = 451$) SEM	Personal hygiene, green trust, and hedonic motivations (pleasure, ease, novelty) increase continued intention; risks (performance, psychological) reduce it. Green trust partially mediates hygiene–intention link.
Schmidt and Saraceni (2024)	Theory of planned behavior Anthropomorphism	Survey (n = 450) SEM	Anthropomorphic drones improve attitudes, norms, and intention via perceived control.
Mahmoud and Mahroof (2025)	UTAUT2, Diffusion of Innovations	Big data analysis ($n =$ 2337 social media posts)	Public concerns span safety, ethics, practicality, and distrust; sentiment is mostly negative, yet some support innovation—especially in extreme contexts.
Our Study	UTAUT 2 Risk theory (technology, privacy, environment), Transformative marketing (well-being)	2x2x2 between-subject experiment design ($n =$ 3212) PROCESS	Performance expectancy, social influence, well-being, and environmental concern boost intention; risks (privacy, cyber, physical) reduce it. Moderators: environmental concern, product criticality.

Acceptance Model (TAM; (Davis, 1989), and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2; (Venkatesh and Thong, 2012), often combined with other relevant theories like innovation resistance, resource matching, and anthropomorphism.

The main consensus across studies is that privacy concerns remain a consistent barrier to adoption, as consumers express fear over surveillance and data misuse (Khan et al., 2019; Jiang et al., 2023). Conversely, performance expectancy and perceived environmental benefits positively influence attitudes and behavioral intentions, especially when the delivery service projects a strong green image (Holzmann et al., 2021; Hwang and Kim, 2019). Social influence, though less consistently significant, can enhance adoption by improving perceived social status or conformity with peer expectations. The importance of resource alignment and service quality is also highlighted (Jiang et al., 2023).

Recent work has begun to introduce moderating variables such as demographics (Hwang and Kim, 2019), innovation resistance (Sham et al., 2023), and contextual fit (Lim et al., 2024), adding nuance to traditional models. Hedonic factors influence trust, intentions to use and positive word-of-mouth recommendations (Lim et al., 2024). Novel factors like anthropomorphism have also been shown to enhance trust and control, thereby increasing adoption intentions (Schmidt and Saraceni, 2024).

Despite valuable insights, the literature exhibits several key gaps that this article aims to address. First, much of the literature still treats benefits and risks in isolation, often neglecting their potential interaction or moderating conditions. Second, well-being and trust as key outcomes or mediators are not investigated. Yet well-being and trust are critical to transformative consumer research and can significantly influence adoption of emotionally salient technologies like AI-automated delivery drones. Third, real-world complexities such as cybersecurity threats, physical accidents, or product criticality (e.g., medical vs. retail goods) and user well-being are not investigated. Most prior studies treat adoption drivers like risk and benefit perceptions as independent variables without accounting for their interaction or the conditional nature of user evaluations. For example, the joint effects of cyberattacks, physical safety concerns, and environmental values have not been explored together. Furthermore, real-world decision complexity has not been taken into account by integrating cognitive (e.g., performance expectancy), affective (e.g., well-being), and contextual (e.g., environmental concern, criticality) components within a unified framework. Fourth, although some studies recognize the impact of demographics or innovation resistance, product criticality (e.g., delivering medicine vs. groceries) and environmental concerns remain largely unexplored as boundary conditions or moderators. Finally, the literature gives limited attention to negative scenarios, such as AI-automated delivery drone malfunctions, cyberattacks, physical accidents or data breaches.

To address these gaps, our study incorporates a 2x2x2 design that tests the effects of cyberattacks, physical accidents, and product criticality, offering a more realistic, complex model of user appraisal. Our study expands the UTAUT2 (Venkatesh and Thong, 2012) model to include well-being, revealing how it mediates the link between both perceived benefits and risks and behavioral intention. Our work also tests the moderating effects of environmental concerns and product type/criticality, particularly in life-critical or health-related delivery contexts.

2.3. UTAUT2 and theoretical justification

We adopt the UTAUT2 (Venkatesh and Thong, 2012) as the baseline model for technology adoption, which is well-suited for non-organizational consumer settings. This model has gained popularity due to its simplicity and strong explanatory power in predicting users' intentions to adopt new technologies (King and He, 2006). It suits for technology adoption in non-organizational contexts, particularly among end users (King and He, 2006). In this study, we focus specifically on performance expectancy and social influence, two core constructs that have demonstrated consistent predictive power across digital innovation contexts. Performance expectancy is theoretically grounded in expectancy-value theory, reflecting the instrumental benefits consumers perceive from adopting a technology (Davis, 1989; Venkatesh and Thong, 2012). In the context of AI-automated drone delivery, performance expectations are especially salient as consumers anticipate improvements in speed, reliability, and convenience (Kapser and Abdelrahman, 2020). Social influence stems from subjective norm theory and reflects the perceived expectations of important others (Ajzen, 1991). Its relevance is amplified in contexts where the novelty of AI-automated drone delivery not only triggers hedonic motivation but also shapes public attitudes, especially in unfamiliar or high-risk environments where social perception and perceived innovativeness play a decisive role in early adoption (Mahmoud and Mahroof, 2025; Shahzad et al., 2024). We deliberately excluded other UTAUT2 variables such as effort expectancy and facilitating conditions for both theoretical and contextual reasons. These constructs are more applicable to mature technologies or repeated-use systems. AI-automated drone delivery, still in an emergent phase, involves minimal user interface or infrastructure requirements from the consumer's side. Thus, consumers are unlikely to base their adoption intention on ease of use or technical support (as also suggested by Venkatesh et al., 2016 for exploratory scenarios). This theoretical focus allows us to enrich the UTAUT2 framework with additional constructs (i.e., perceived risk, privacy concern, and well-being) that are especially pertinent in emerging, autonomous, and emotionally salient technologies. Our extension is theoretically motivated by the unique attributes of AI-automated delivery drones. Unlike familiar technologies, drones provoke affective responses tied to well-being, ecological identity, and trust in automation (Shahzad et al., 2024). In line with transformative consumer research (Davis and Pechmann, 2013; Su et al., 2014), we incorporate well-being as a mediating outcome between technological perceptions and adoption behavior as AI-automated delivery drones are designed to improve user well-being by reducing traffic, enhancing physical safety during deliveries, improving air quality (Choe et al., 2021). Additionally, we also draw from perceived risk theory (Featherman and Pavlou, 2003) to integrate privacy and technology risks—dimensions particularly salient in the AI-automated drone delivery context (Gefen and Straub, 2004; Park et al., 2018; Venkatesh and Thong, 2012). This comprehensive approach allows us to better understand the multifaceted nature of technology adoption, particularly in the context of emerging technologies like AI-automated delivery drones, and to address the key factors that drive or hinder user acceptance.

3. Hypotheses

The hypotheses section explores the key factors influencing the adoption of AI-automated delivery drones. It begins with the mediating role of well-being, emphasizing how positive emotions and experiences from using AI-automated delivery drone technology can enhance quality of life and adoption intent. Specifically, it examines benefits such as performance expectancy and social influence, highlighting how utilitarian advantages like time savings and social recognition shape behavioral intentions through well-being. Risks, including perceived technological and privacy threats, are then discussed for their negative impact on user perceptions and willingness to adopt. The analysis also considers AI-automated delivery drone failures, such as physical accidents and cyberattacks, and their effects on perceived risk and performance. Finally, the moderating roles of environmental concern and product criticality are assessed, showing how sustainability values and the importance of delivered goods influence adoption and well-being.

3.1. Benefits associated with AI-automated drone delivery on well-being

Well-being functions as a pivotal mediator through which perceived benefits of AI-automated drone delivery translate into users' intention to adopt the technology. This mediating role is grounded in its multidimensional structure (i.e., hedonic, eudaimonic, and psychological well-being), which captures both the immediate and lasting impact of technological innovations on individuals' emotional and cognitive evaluation of their lives (Diener et al., 2018; Ryan and Deci, 2001). In the context of technology adoption, well-being reflects the extent to which a new service or product enhances users' emotional and cognitive evaluations of their life (Chitturi et al., 2008; Diener, 1984). This includes not only momentary pleasure (e.g., fast delivery or convenience) but also more enduring benefits such as reduced stress from sustainable consumption or health-related efficiencies (Su et al., 2014; Meyer-Waarden et al., 2021; Rozanski and Kubzansky, 2005). Hedonic well-being is activated when AI-automated delivery drones provide speed, convenience, or enjoyment in the user experience, resulting in immediate positive affect (Shahzad et al., 2024; Voss et al., 2003; Dhar and Wertenbroch, 2000). Eudaimonic well-being is reinforced when consumers perceive that using environmentally friendly AI-automated delivery drones aligns with their values of sustainability and social responsibility (Huta and Ryan, 2010). Furthermore, psychological well-being may be supported when consumers feel autonomous and in control through frictionless, modern delivery options (Davis and Pechmann, 2013; Ryff, 1989).

The literature establishes that when new services contribute positively to these dimensions, by facilitating momentary pleasure, aligning with personal values, or enhancing autonomy, users are more likely to exhibit favorable behavioral responses (Chitturi et al., 2008; Shahzad et al., 2024; Zhong and Mitchell, 2012). Among the most salient antecedents of well-being in the context of AI-automated drone delivery is performance expectancy, defined as the perceived capacity of the technology to enhance task efficiency (Venkatesh and Thong, 2012). AI-automated delivery drones offer tangible utilitarian benefits, such as reduced delivery times, avoidance of urban congestion, and improved logistical efficiency, which directly satisfy consumers' need for convenience and speed (Holzmann et al., 2021; Hwang et al., 2019). These features contribute to hedonic well-being by generating immediate pleasure and affective satisfaction during the service experience (Voss et al., 2003). Furthermore, when users perceive that AI-automated delivery drones contribute to sustainability, by lowering emissions and energy use, eudaimonic well-being is activated, as the service resonates with deeper values and aspirations for responsible consumption (Gao and Bai, 2014; Huta and Ryan, 2010). The reduction in physical effort and the seamless nature of AI-automated drone usage also foster psychological well-being by promoting autonomy, control, and a sense of time mastery (Davis and Pechmann, 2013; Ryff, 1989).

Social influence, the extent to which adoption is shaped by others' expectations, reinforces this effect by fulfilling the need for social approval, inclusion, and self-esteem (Venkatesh and Thong, 2012; Bandura, 1989). When the use of AI-automated delivery drones is perceived as modern, responsible, or socially valorized, individuals derive emotional gratification from peer endorsement and identity signaling (Meyer-Waarden et al., 2021; Sweeney and Soutar, 2001). This satisfaction contributes to both hedonic well-being (e.g., joy, pride) and eudaimonic well-being (e.g., alignment with social norms or group values), reinforcing the sense that technology use enhances not only functional life aspects but also social and moral self-concepts.

As supported by prior research, such positive evaluations of well-being significantly influence the adoption of innovative or disruptive technologies (Ayadi et al., 2017; Diener and Chan, 2011). When performance expectancy and social influence both elevate users' perceived quality of life, they reinforce well-being, which in turn drives the formation of favorable behavioral intentions toward AI-automated drone delivery. Thus, the benefits associated with AI-automated drone delivery are not only direct predictors of intention but also indirectly affect adoption by first enhancing users' subjective well-being, hence we hypothesize:

H1a. The benefits associated with AI-automated drone delivery, namely performance expectancy and social influence, have a positive indirect effect on behavioral intention through user well-being.

3.2. Risks associated with AI-automated drone delivery on well-being

While AI-automated drone delivery offers notable advantages, its adoption remains contingent upon users' appraisal of associated risks, particularly in terms of technological reliability, physical safety, and personal privacy. These perceptions, when negative, do not merely affect behavioral intentions directly; they also undermine user well-being, thereby exerting an indirect detrimental effect on technology acceptance. This pathway underscores the psychological toll that risk anticipation imposes on users' affective and cognitive states (Meyer-Waarden et al., 2021).

Perceived technology risk, as conceptualized in the literature, encompasses concerns about potential adverse outcomes when engaging with an unfamiliar or complex system (Cox and Rich, 1964; Featherman and Pavlou, 2003). In the context of AI-automated drone delivery, two dimensions are particularly salient: functional risk, or the fear that the AI-automated delivery drone may malfunction or fail to perform its intended function, and physical risk, involving concerns about crashes, navigation errors, or property damage (Forsythe and Shi, 2003). These risks, whether experienced or anticipated, heighten users' sense of uncertainty and diminish their perceived ability to interact safely and effectively with the technology (Mahmoud and Mahroof, 2025; Mathew et al., 2021; Hwang and Choe, 2019).

The negative impact of these risks on well-being is multifaceted. First, they elicit emotional distress, including anxiety and fear, which directly impair hedonic well-being by reducing users' capacity to experience pleasure and comfort in relation to the service (Su et al., 2014; Rozanski and Kubzansky, 2005). Second, they threaten psychological well-being by undermining perceived autonomy and control, key factors that foster feelings of security and life satisfaction (Ryan and Deci, 2001; Ryff, 1989). A service perceived as unpredictable or unsafe fails to support a stable and self-directed user experience, which is crucial for maintaining a positive subjective state. These emotional and cognitive disturbances collectively erode the user's overall well-being.

Beyond technological and physical safety, privacy concerns constitute a critical category of perceived risk in AI-automated drone delivery (Koh et al., 2023; Leon et al., 2021). They refer to users' apprehension about how personal data (such as location, identity, or behavioral patterns) may be collected, stored, or misused (Malhotra et al., 2004; Phelps et al., 2000). These concerns are especially salient in the case of AI-automated drones equipped with cameras, sensors and recognition systems, which can evoke perceptions of surveillance or unauthorized data sharing (Pande and Taeihagh, 2021) Taeihagh. Users may fear that AI-automated delivery drones flying over private property could capture imagery, track delivery locations, or share sensitive information with third parties (Gurumurthy and Kockelman, 2020; Khan et al., 2019). These privacy apprehensions generate emotional discomfort and feelings of vulnerability, which diminish both hedonic well-being (through anxiety and fear) and psychological well-being (through reduced perceptions of control and safety) (Meyer-Waarden et al., 2021). This aligns with the privacy calculus theory, which posits that individuals weigh perceived privacy intrusions against potential benefits before adopting a new technology (Featherman and Pavlou, 2003; Hong and Thong, 2013).

Collectively, functional, physical, and privacy-related risks represent an interrelated set of stressors that undermine users' overall well-being. A service perceived as unreliable, unsafe, or invasive fails to support a stable, autonomous, and emotionally positive user experience, critical components of subjective well-being (Su et al., 2014; Rozanski and Kubzansky, 2005). As established in prior research, diminished well-being significantly reduces the likelihood that individuals will form favorable intentions to adopt new technologies (Zhong and Mitchell, 2012; Chitturi et al., 2008).

Therefore, we argue that risks associated with AI-automated drone delivery, whether concerning technology or privacy, weaken adoption intention indirectly by undermining user well-being, which serves as a key mediating variable in this process. Thus we posit:

H1b. The risks associated with AI-automated drone delivery, specifically perceived technology risk and privacy concerns, have a negative indirect effect on behavioral intention through user well-being.

3.3. AI-automated delivery drone failures

3.3.1. Physical accidents

As AI-automated delivery drones increasingly occupy public and private airspace, concerns about physical accidents have emerged as a salient barrier to adoption (Mahmoud and Mahroof, 2025; Luppicini and So, 2016). Since AI-automated drone technology is still evolving, users worry about technical malfunctions, loss of navigation control, and the possibility of collisions with people, animals, or property (Choe et al., 2021). These incidents are not purely hypothetical: growing reports of AI-automated drone crashes and near misses have received media attention, heightening public sensitivity to physical risks and reinforcing a narrative of operational unreliability (Osakwe et al., 2022).

The perception of physical accidents, even when rare, can significantly elevate technology-related risk perceptions. According to risk appraisal theory, when users are exposed to cues signaling physical danger such as AI-automated drone malfunctions or near collisions, they tend to generalize this into broader skepticism about the system's trustworthiness and safety (Sah et al., 2021). This perception not only increases the overall perceived risk associated with using AI-automated drones but also undermines performance expectancy, i.e., the belief that the technology will deliver efficient, reliable, and beneficial outcomes (Venkatesh and Thong, 2012; Martins et al., 2014). Hence, we propose the following hypotheses:

H2a. Physical accidents have a positive effect on perceived technology risk.

H2b. Physical accidents have a negative effect on performance expectancy.

3.3.2. Cyberattacks

In the context of AI-automated delivery drones, cyberattacks represent a critical emerging threat that undermines both operational reliability and data security. These attacks can involve hacking AI-automated drone navigation systems, interfering with flight paths, or stealing data related to users' locations, identities, or delivered goods (Martins et al., 2014). Such breaches not only create functional disruption risks, such as missed or misrouted deliveries, but also provoke concerns about the safety of individuals who may be harmed by malicious control over AI-automated drones (Choe et al., 2021).

From a risk perception standpoint, the awareness of AI-automated drone-targeted cyberattacks, increasingly reported in media and public discourse, heightens both perceived technology risk and privacy concerns. Users may feel that they are unable to control how their data is accessed or whether the technology will perform securely and predictably (Hwang et al., 2019). This is particularly salient in light of AI-automated drones' capabilities to collect geolocation and visual data, which can be exploited if not adequately protected. Thus, cyberattacks intensify both technological fears and informational vulnerabilities—two key barriers to technology acceptance (Featherman and Pavlou, 2003; Malhotra et al., 2004). Furthermore, these fears undermine performance expectancy, as users begin to doubt the AI-automated drone's ability to deliver goods reliably, securely, and without compromise. Consistent with the technology threat-avoidance model and prior work on trust erosion in automated systems, heightened cyber-related risk perceptions reduce trust in the system's performance and dependability (Choe et al., 2021; Martins et al., 2014). Accordingly, we propose:

H3a. Cyberattacks have a positive effect on perceived technology risk.

H3b. Cyberattacks have a positive effect on privacy concerns.

H3c. Cyberattacks have a negative effect on performance expectancy.

3.4. Sustainability of AI-automated drone delivery

Environmental concerns reflect consumers' awareness of ecological degradation and their belief that personal choices (such as transportation habits) can impact sustainability (Mainieri et al., 1997; Stern, 1992; Kinnear et al., 1974). As global environmental awareness has grown, consumers increasingly favor technologies seen as eco-friendly, low-carbon, and energy-efficient (Hartmann and Apaolaza-Ibáñez, 2012; Chang, 2011).

In this context, AI-automated delivery drones optimized for short distances are perceived as sustainable alternatives to gasoline-based delivery vehicles, emitting significantly less CO_2 (Figliozzi, 2017; Goodchild and Toy, 2018; Park et al., 2018; Stolaroff et al., 2018). These green perceptions enhance both the symbolic and functional value of AI-automated drone technology and reduce cognitive dissonance associated with adopting new technologies (Festinger, 1954), thereby improving user well-being (Mahmoud and Mahroof, 2025; Mathew et al., 2021; Chiang et al., 2019; Hwang et al., 2019).

From a moderation standpoint, users with strong environmental concerns are more likely to derive psychological and emotional benefits (such as pride, identity alignment, and satisfaction) when using sustainable technologies (Hartmann and Apaolaza-Ibáñez, 2012). Thus, environmental concern is expected to strengthen the positive influence of performance expectancy and social influence on well-being. At the same time, these concerns may serve a protective cognitive function, buffering the negative emotional impacts of perceived risks (e.g., privacy loss, safety concerns), by framing AI-automated drone use as a morally or socially justified behavior despite imperfections. Thus:

H4a. Environmental concerns strengthen the positive relationship between the benefits of AI-automated delivery drones (i.e., performance expectancy and social influence) and user well-being.

H4b. Environmental concerns strengthen the negative relationship between the risks of AI-automated delivery drones (i.e., perceived technology risk and privacy concerns) and user well-being.

3.5. Product criticality in AI-automated drone delivery

Product criticality is the degree of psychological or functional significance a product has on the consumer during the purchase and usage stages (Hagtvedt and Patrick, 2009). This is inclusive of the utilitarian significance of the product (i.e., necessity, immediacy, consequences of a delay) as well as any psychological salience, such as personal relevance, emotional salience, or associated perceived vulnerability related to the product (Zaichkowsky, 1985).

Product criticality affects how users process information, assess technology performance, and evaluate emotional outcomes, especially in contexts involving uncertainty or risk (Cacioppo et al., 1986; Zaichkowsky, 1985). When applied to AI-automated drone delivery, users may respond differently depending on whether the product being delivered is of low criticality (e.g., groceries or everyday goods) or high criticality (e.g., medical supplies or life-dependent items). In high-criticality scenarios, the stakes are higher: a failure in delivery can have serious implications for health or safety, leading consumers to adopt a more cautious and risk-averse stance.

As such, product criticality can moderate the relationship between user well-being and behavioral intention. When product criticality is low, well-being derived from fast, convenient, and environmentally friendly delivery may significantly enhance behavioral intentions. In contrast, when product criticality is high, users may downplay positive affect and instead focus on risk, reliability, and safety, thereby weakening the impact of well-being on behavioral adoption intents to use AI-automated delivery drones. This aligns with research in risk-averse decision-making and high-involvement product processing (Hagtvedt and Patrick, 2009; Dhar and Wertenbroch, 2000). We therefore hypothesize:

H5. Product criticality negatively moderates the relationship between user well-being and behavioral intentions to use AI-automated delivery drones.

Fig. 1 represents our research model.

4. Methodology

4.1. Research design

We employed a between-subjects experimental design to establish causal relationships between contextual factors and consumer responses to AI-automated drone-based last-mile delivery. Experimental designs are widely recognized as the gold standard for testing causal hypotheses, as they enable researchers to manipulate independent variables and isolate their effects on dependent variables while controlling for confounding factors (Shadish et al., 2001).

In our 2x2x2 between-subjects design, we manipulated three independent variables to examine their effects on participants' perceptions and responses. The first variable was the product category, which we varied by assigning participants to scenarios involving either the delivery of grocery retail products or medical drugs. This manipulation allowed us to investigate the impact of the criticality of the product on the dependent variables. The second variable was the occurrence of a physical accident during delivery. Participants were either exposed to a scenario where a physical accident involving the AI-automated drone occurred or to one where no such accident took place, enabling us to assess how physical mishaps influence outcomes. The third variable was the presence or absence of a cyberattack during delivery, with participants either encountering a scenario in which a cyberattack occurred or one where it did not.

To increase ecological validity, each condition was embedded in a narrative vignette or scenario. For example, participants assigned to the control condition read: "AI-automated drone delivery is a form of delivery that uses aerial drones to transport packages to recipients. An AI-automated delivery drone is a drone largely automated specifically designed for this logistical activity with limited adaptive intelligence. Imagine the following specific situation: (1) You are having your groceries delivered by an AI-automated delivery drone. (2) During the flight, no physical accident involving the AI-automated drone occurred. (3) During the flight, no cyberattack against the AI-automated drone occurred." By manipulating these three factors across eight different conditions, we aimed to understand how the combination of product criticality, physical accidents, and cyberattacks affects the perceptions and behaviors of the subjects in the context of AI-automated drone deliveries.

4.2. Sample characteristics

We conducted an online survey with a convenience sample of 3212 respondents from France, aiming for approximately 400 participants per condition in our 2x2x2 between-subjects experimental design. The mean

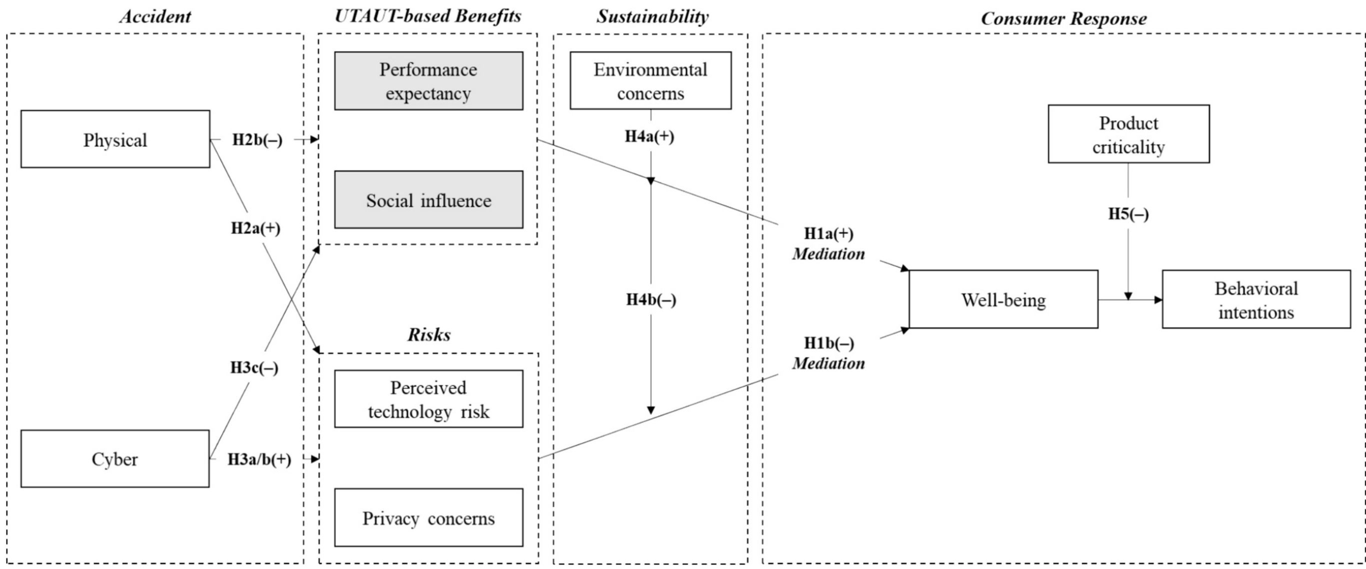

Fig. 1. Research model.

age of participants was 30.8 years (SD = 14.5), which is notably younger than the national average of 42.6 years.[1] The sample consisted of 56.6% women, slightly higher than the national average of 51.6%.[2] Additionally, 79.7% of respondents reported living in or around cities, closely aligning with the national statistic of 78.7%.[3] While the sample is largely representative in terms of gender and urban residency, the younger age profile and convenience sampling method suggest a potential skew in representativeness, with a higher proportion of younger individuals compared to the overall French population.

Following Soni et al. (2021), our study focuses on Generation Z, a tech-savvy cohort widely used in technology adoption research for comparability. While not representative of the entire population, Gen Z constitutes a relevant market segment for AI-automated delivery drones and they are typically more tech-savvy and thus more open to AI-automated drones (Mcmillan and Morrison, 2006). This focus is also supported by Venkatesh and Thong (2012), who emphasize age as a key factor in technology acceptance, with younger, digitally native users adapting more readily than older generations.

4.3. Measurement instruments

All measurement scales used in this study were adapted from established literature. To assess environmental concerns, we used the scale developed by Chang (2011), with items such as "*I think AI-automated delivery drones would be good for the environment.*" Performance expectancy, social influence, and behavioral intention to use were measured using scales derived from the UTAUT2 model (Venkatesh and Thong, 2012). Examples include "*AI-automated delivery drones would make my daily life easier*" for performance expectancy, "*People who influence my behavior think I should use AI-automated delivery drones in the future*" for social influence, and "*I am likely to use AI-automated delivery drones in the future*" for behavioral intentions. Perceived technology risks were measured using the scale from Meuter et al. (2005), including items like "*I am apprehensive about the use of AI-automated drone delivery technology*." Privacy concerns were assessed using Malhotra et al. (2004) scale, with statements such as "*AI-automated delivery drones could cause serious privacy issues for my personal data.*" To evaluate user well-being, we used the scale from Meyer-Waarden and Cloarec (2022), featuring items like "*AI-automated delivery drones would improve my sense of well-being.*" All scales were measured using a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Detailed information on the scales, items used, and their psychometric properties can be found in Table 2.

4.4. Assessment of the measurement model

We conducted a confirmatory factor analysis to evaluate the measurement model, which demonstrated a good fit based on standard fit indices: chi-square (χ^2) = 3169.466, degrees of freedom (df) = 278, root mean square error of approximation (RMSEA) = 0.057, comparative fit index (CFI) = 0.961, and Tucker–Lewis index (TLI) = 0.954. The psychometric properties of the scales were satisfactory. Reliability was confirmed with Cronbach's alpha (α) values exceeding 0.70. Convergent validity was supported, as average variance extracted (AVE) values were greater than 0.50 (see Tables 2 and 3). Additionally, discriminant validity was assessed using the heterotrait-monotrait ratio of correlations (HTMT), with all constructs falling below the 0.85 threshold, thereby confirming discriminant validity (Table 3).

4.5. Common method variance

We established that common method variance was not an issue for the study (Podsakoff et al., 2003). The author used the ConMET package (Schutter, 2021) to test the competitive models where items from two constructs load on the same latent variable. All the configurations significantly decreased the fit of the measurement model (i.e., χ^2 significantly increases with $p < .001$), as shown in Table 4. In addition, the authors tested the performance of Harman's single factor (Harman, 1967), and the results indicated that it performed poorly compared to the measurement model ($p < .001$).

4.6. Post hoc power analysis

Post hoc power analysis can determine whether a sample size is sufficient to provide robust estimates (Moshagen and Erdfelder, 2016). We used the semPower package (Moshagen and Bader, 2024) to assess the power of the analysis. With an RMSEA of 0.047, a sample size of 400, 71 degrees of freedom, and an alpha of 0.05, the computation indicates that the power ($b > 0.99$) is satisfactory (i.e., > 0.80). Fig. 2 illustrates the corresponding central and noncentral χ^2 distributions.

[1] https://www.insee.fr/fr/statistiques/2381476
[2] https://www.insee.fr/fr/statistiques/2381474
[3] https://www.insee.fr/fr/statistiques/5347845

Table 2
Psychometric properties of the measurement scales.

	α	AVE
Performance expectancy (Venkatesh and Thong, 2012)	0.93	0.78
AI-automated delivery drones would be a good assistant in my daily life		
AI-automated delivery drones would save me useful time in my daily life		
AI-automated delivery drones would make my daily life easier		
AI-automated delivery drones would increase my efficiency in my daily life		
Social influence (Venkatesh and Thong, 2012)	0.91	0.77
People who are important to me think I should use AI-automated delivery drones in the future		
People who influence my behavior think I should use AI-automated delivery drones in the future		
People who are important to me support me in using AI-automated delivery drones in the future		
Perceived technological risk (Meuter et al., 2005)	0.89	0.59
I am apprehensive about the use of AI-automated drone delivery technology		
I would avoid AI-automated drone delivery technology because I am not familiar with it		
I would be reluctant to use AI-automated delivery drone technology for fear of losing control that I cannot correct		
I am concerned that AI-automated delivery drones may cause dangerous side effects if they malfunction or are misused		
I am concerned that AI-automated delivery drones are not completely safe and may pose potential physical risks		
I am concerned that AI-automated delivery drones make me feel like I am losing too much control over the technologies		
Privacy concerns (Malhotra et al., 2004)	0.90	0.72
AI-automated delivery drones could cause serious privacy issues for my personal data		
I would be very concerned about the privacy issues of my personal data related to AI-automated delivery drones		
The privacy of my personal data related to AI-automated delivery drones would be very important		
I would be concerned about the threats that AI-automated delivery drones could pose to the privacy of my personal data		
Environmental concerns (Chang, 2011)	0.93	0.81
I think AI-automated delivery drones would be good for the environment		
I think that AI-automated delivery drones could help slow down the deterioration of the environment		
I think that AI-automated delivery drones would be effective in reducing pollution		
Well-being (Meyer-Waarden et al., 2021)	0.92	0.80
AI-automated delivery drones would improve my quality of life to make it ideal		
AI-automated delivery drones would improve my sense of well-being		
AI-automated delivery drones would improve my sense of happiness		
Behavioral intention to use (Venkatesh and Thong, 2012)	0.95	0.87
In view of their advantages, I intend to use AI-automated delivery drones in the future		
Considering their advantages, if I had access to AI-automated delivery drones, I intend to use them to deliver my orders		
I am likely to use AI-automated delivery drones in the future		

Table 3
Descriptive statistics and HTMT ratios of coefficients.

	M	SD	PE	SI	PTR	PC	ENV	WB	BI
PE	4.08	1.52							
SI	3.24	1.35	0.59						
PTR	4.52	1.36	0.44	0.43					
PC	4.98	1.35	0.18	0.18	0.51				
ENV	4.44	1.46	0.49	0.35	0.27	0.12			
WB	3.21	1.43	0.73	0.62	0.40	0.19	0.52		
BI	3.85	1.64	0.75	0.65	0.60	0.30	0.52	0.71	

Notes. PE: performance expectancy, SI: social influence, PTR: perceived technology risk, PC: privacy concerns, WB: well-being, BI: behavioral intention to use, ENV: environmental concerns, CRITIC: product criticality.

Table 4
Common method variance estimation.

	χ^2	df	cfi	rmsea	srmr	$\Delta\chi^2$
Proposed model	3169.466	278	0.961	0.057	0.035	
PE and SI	8070.032	284	0.894	0.092	0.058	4900.567***
PE and PTR	11,683.061	284	0.845	0.112	0.106	8513.595***
PE and ENV	9506.642	284	0.874	0.101	0.063	6337.177***
PE and PC	12,418.123	284	0.835	0.115	0.114	9248.657***
PE and WB	7194.092	284	0.906	0.087	0.045	4024.626***
PE and BI	8330.703	284	0.890	0.094	0.047	5161.237***
SI and PTR	9529.624	284	0.874	0.101	0.096	6360.159***
SI and ENV	10,537.581	284	0.860	0.106	0.084	7368.115***
SI and PC	12,433.616	284	0.835	0.115	0.114	9264.15***
SI and WB	7599.414	284	0.900	0.090	0.052	4429.948***
SI and BI	7443.976	284	0.903	0.089	0.052	4274.51***
PTR and ENV	11,047.538	284	0.854	0.109	0.106	7878.072***
PTR and PC	9573.628	284	0.874	0.101	0.068	6404.162***
PTR and WB	11,384.643	284	0.849	0.110	0.112	8215.177***
PTR and BI	9535.864	284	0.874	0.101	0.085	6366.398***
ENV and PC	12,666.135	284	0.831	0.117	0.128	9496.669***
ENV and WB	9175.197	284	0.879	0.099	0.059	6005.731***
ENV and BI	9260.585	284	0.878	0.099	0.064	6091.119***
PC and WB	12,945.953	284	0.828	0.118	0.177	9776.487***
PC and BI	15,413.277	284	0.794	0.129	0.179	12,243.811***
WB and BI	7747.539	284	0.898	0.090	0.051	4578.073***
Harman's one factor	36,401.661	299	0.509	0.194	0.142	33,232.195***

Notes. ***$p < .001$, PE: performance expectancy, SI: social influence, PTR: perceived technology risk, PC: privacy concerns, WB: well-being, BI: behavioral intention to use, ENV: environmental concerns.

4.7. Method of analysis

To implement the research model and test our hypotheses, we used PROCESS for R Version 4.0.1, a statistical tool designed for path analysis and moderation/mediation analysis (Hayes, 2021). This method is particularly well-suited for our analysis because it allows for the examination of complex models involving multiple mediators, moderators, and their interactions. Unlike traditional regression analysis, PROCESS provides a streamlined and efficient way to test hypotheses involving conditional indirect effects, which is critical for understanding the nuanced relationships in our model. Additionally, PROCESS offers the ability to generate bootstrap confidence intervals, which enhances the robustness and reliability of the results.

We implemented our own custom syntax in PROCESS, specifying 5000 bootstrap samples to ensure accurate estimation of the indirect effects and their confidence intervals. The custom syntax was tailored to accommodate the specific needs of our model, including multiple mediators, covariates, and moderators.

5. Results

5.1. Manipulation checks

Respondents in the medical drug delivery condition (M = 4.77, SD = 1.87) reported significantly higher product criticality compared to those in the grocery retail product delivery condition (M = 4.63, SD = 1.81; $t_{(3210)} = -2.12$, $p = .034$). A t-test for the manipulation check on physical accidents revealed that participants exposed to a physical accident scenario (M = 5.24, SD = 1.53) perceived higher risks than those in the no-accident condition (M = 5.09, SD = 1.58; $t_{(3210)} = -2.75$, $p = .006$). Similarly, under the cyber-attack condition, the situation was perceived as significantly riskier (M = 5.56, SD = 1.45) than under the no cyber-attack condition (M = 5.43, SD = 1.50; $t_{(3210)} = -2.48$, $p = .013$). These results confirm the effectiveness of our experimental manipulations, indicating that respondents distinctly perceived the different conditions.

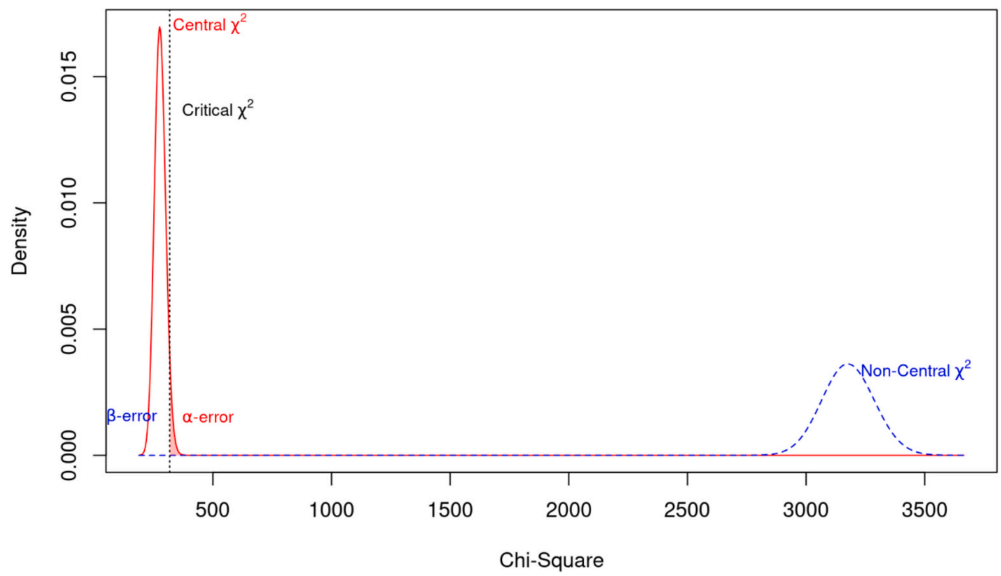

Fig. 2. Associated central and non-central χ^2 distribution

Notes. The image shows two overlaid density curves representing chi-square distributions, which are commonly used in statistical hypothesis testing. The red curve represents the central chi-square distribution, which is the distribution of chi-square values we would expect by chance when the null hypothesis is true. The blue dashed curve represents the noncentral chi-square distribution, which reflects the distribution of chi-square values when the null hypothesis is not true, i.e., when there is a true effect. The vertical line likely represents the chi-square critical value at the 0.05 alpha level. This is the cutoff point where, if the observed chi-square statistic is to the right of this line, the result would be considered statistically significant, leading to the rejection of the null hypothesis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.2. Hypotheses testing

5.2.1. Benefits associated with AI-automated drone delivery on well-being

The mediation analysis (Table 5) provides support for hypothesis H1a. Specifically, the indirect effect of performance expectancy on behavioral intention, mediated by well-being, is both positive and statistically significant (b = 0.09, $p < .05$, 95% CI = [0.0677, 0.1199]). Similarly, the indirect effect of social influence on behavioral intention through well-being is also positive and significant (b = 0.05, p < .05, 95% CI = [0.0179, 0.0784]).

5.2.2. Risks associated with AI-automated drone delivery on well-being

Consistent with hypothesis H1b, the analysis reveals that the indirect effect of privacy concerns on behavioral intention, via well-being, is negative and statistically significant (b = −0.05, p < .05, 95% CI = [−0.0797, −0.0304]). However, contrary to expectations, the indirect effect of perceived technology risk on behavioral intention is positive rather than negative, although it remains statistically significant (b = 0.03, p < .05, 95% CI = [0.0068, 0.0574]). Therefore, H1b receives only partial support.

5.2.3. AI-automated delivery drone failures

The results (Table 6) support hypothesis H2a, as physical accidents were found to significantly increase perceived technology risk (b = 0.13, $p < .01$). Hypothesis H2b is also supported, with physical accidents shown to significantly decrease performance expectancy (b = −0.21, $p < .001$). These findings suggest that safety concerns meaningfully influence users' perceptions of the technology. The data also support hypothesis H3a, with cyberattacks significantly increasing perceived technology risk (b = 0.13, p < .01). Hypothesis H3b is supported as well, as cyberattacks were found to increase privacy concerns (b = 0.19, p < .001). In addition, hypothesis H3c is supported, with cyberattacks having a significant negative effect on performance expectancy (b = −0.18, p < .001).

5.2.4. Sustainability of AI-automated drone delivery

The moderation analysis yielded insightful results regarding the impact of environmental concerns and product criticality on the relationships between key variables. Environmental concerns were found to positively moderate the relationship between the benefits of AI-automated delivery drones—specifically, performance expectancy ($b = 0.02$, $p < .01$) and social influence ($b = 0.02$, $p < .01$)—and well-being, providing support for H4a. This suggests that when users are more concerned about the environment, the positive effects of perceived benefits on their well-being are enhanced.

However, the results for H4b were partially supported. Environmental concerns negatively moderated the relationship between perceived technology risk and well-being ($b = -0.03$, $p < .01$), which aligns with the hypothesis. Conversely, the interaction term for privacy concerns showed an opposite sign ($b = 0.03$, $p < .01$), indicating that higher environmental concerns unexpectedly reduced the negative impact of privacy concerns on well-being, contrary to what was hypothesized.

5.2.5. Product criticality in AI-automated drone delivery

Finally, the analysis confirmed that product criticality negatively moderates the relationship between well-being and behavioral intention to use AI-automated delivery drones (H5: $b = -0.08$, $p < .001$). This finding suggests that when the criticality of the product being delivered is high, the positive effect of well-being on the intention to use AI-

Table 5
Mediation analysis.

Path	Indirect effect	SE	95% CI Lower	95% CI Upper
PE → WB → BI	0.09*	0.01	0.0677	0.1199
SI → WB → BI	0.05*	0.02	0.0179	0.0784
PTR → WB → BI	0.03*	0.01	0.0068	0.0574
PC → WB → BI	−0.05*	0.01	−0.0797	−0.0304

BI = Behavioral Intention to Use; WB = Well-being; PE = Performance Expectancy; SI = Social Influence; PTR = Perceived Technology Risk; PC = Privacy Concerns.

[*] $p < .05$.

Table 6
Estimation of the research model.

	Benefits		Risks		Response	
	PE	SI	PTR	PC	WB	BI
Accidents						
Physical	−0.21***		0.13**			
Cyber	−0.18***		0.13**	0.19***		
Focal variables						
PE					0.32***	0.36***
SI					0.16***	0.23***
PTR					0.11*	−0.28***
PC					−0.19***	−0.05***
WB						0.29***
Interactive effects						
ENV					-.02^{ns}	
PE x ENV					0.02**	
SI x ENV					.02**	
PTR x ENV					−0.03**	
PC x ENV					0.03***	
CRITIC						0.32***
WB x CRITIC						−0.08***
Control variables						
Gender	0.26***	0.31***	−0.54***	−0.27***	0.09*	0.17***
Age	−0.02***	.00^{ns}	−.00^{ns}	-.00^{ns}	-.00**	−0.01***
Location	.02^{ns}	.03^{ns}	−0.13**	-.06^{ns}	-.02^{ns}	.01^{ns}
R^2	0.04	0.01	0.05	0.02	0.56	0.67

*** *Notes*. $p < .001$
** $p < .01$
* $p < .05$, ns: non-significant, PE: performance expectancy, SI: social influence, PTR: perceived technology risk, PC: privacy concerns, WB: well-being, BI: behavioral intention to use, ENV: environmental concerns, CRITIC: product criticality.

automated delivery drones is weakened. These results collectively emphasize the nuanced roles of environmental concerns and product criticality in shaping users' perceptions and behavioral intentions regarding AI-automated delivery drones.

5.3. Moderated mediation analysis

To better understand the psychological mechanisms at play during physical accidents or cyberattacks, we conducted a moderated mediation analysis using the PROCESS macro. In the context of physical accidents (Table 7), for the mediation pathway via performance expectancy and well-being, the index of moderated mediation for environmental concerns was found to be 0.0004, with a 95% confidence interval (CI) of [0.0000, 0.0009], indicating a very small yet statistically significant effect. The indices of conditional moderated mediation were significant for both low and high product criticality, with a stronger negative effect for low product criticality (−0.0603, 95% CI = [−0.0918, −0.0293]) compared to high product criticality (−0.0437, 95% CI = [−0.0682, −0.0213]).

For the mediation pathway via perceived technology risk and well-being, the index of moderated mediation for environmental concerns was similarly small at 0.0003 (95% CI = [0.0000, 0.0007]), suggesting a marginal yet significant effect. The indices of conditional moderated mediation were positive and significant for both levels of product criticality, with a positive effect for low product criticality (0.0369, 95% CI = [0.0093, 0.0652]) and a slightly higher effect for high product criticality (0.0437, 95% CI = [0.0067, 0.0481]).

In the context of cyberattacks (Table 8), for the mediation pathway via performance expectancy and well-being, the index of moderated mediation for environmental concerns was 0.0003, with a 95% confidence interval (CI) of [0.0000, 0.0008], suggesting a small yet statistically significant effect. The indices of conditional moderated mediation revealed a stronger negative effect for low product criticality (−0.0538, 95% CI = [−0.0861, −0.0219]) compared to high product criticality (−0.0390, 95% CI = [−0.0636, −0.0158]).

For the pathway via perceived technology risk and well-being, the index of moderated mediation for environmental concerns was similarly small at 0.0003 (95% CI = [0.0000, 0.0007]). The conditional

Table 7
Results for the moderated mediation with physical accident.

Indirect effect	Environmental concerns	Product criticality	Effect	95% CI		Indices
				Lower	Upper	
PE			−0.07*	−0.1130	−0.0357	
PTR			−0.04*	−0.0633	−0.0093	
PE → WB	Low	Low	−0.02*	−0.0354	−0.0111	Index of moderated mediation for environmental concerns = 0.0004 (95% CI = [0.0000, 0.0009])
	Low	High	−0.02*	−0.0264	−0.008	
	Medium	Low	−0.03*	−0.039	−0.0123	
	Medium	High	−0.02*	−0.0289	−0.0088	Indices of conditional moderated mediation for low product criticality = −0.0603 (95% CI = [−0.0918, −0.0293]) and for high product criticality = −0.0437 (95% CI = [−0.0682, −0.0213])
	High	Low	−0.03*	−0.0417	−0.013	
	High	High	−0.02*	−0.0311	−0.0094	
PTR → WB	Low	Low	.00^{ns}	−0.0005	0.0029	Index of moderated mediation for environmental concerns = 0.0003 (95% CI = [0.0000, 0.0007])
	Low	High	.00^{ns}	−0.0004	0.0021	
	Medium	Low	-.00^{ns}	−0.0022	0.0006	
	Medium	High	-.00^{ns}	−0.0016	0.0004	Indices of conditional moderated mediation for low product criticality = 0.0369 (95% CI = [0.0093, 0.0652]) and for high product criticality = 0.0437 (95% CI = [0.0067, 0.0481])
	High	Low	−0.00*	−0.0045	−0.0001	
	High	High	−0.00*	−0.0033	−0.0001	

* Notes. $p < .05$, ns: non-significant, PE: performance expectancy, PTR: perceived technology risk, WB: well-being.

Table 8
Results for the moderated mediation with cyberattacks.

Indirect effect	Environmental concerns	Product criticality	Effect	95% CI		Indices
				Lower	Upper	
PE			−0.07*	−0.1051	−0.0273	
PTR			−0.04*	−0.0652	−0.0105	
PC			−0.01*	−0.0187	−0.0036	
PE → WB	Low	Low	−0.02*	−0.0331	−0.0082	Index of moderated mediation for environmental concerns = 0.0003 (95% CI = [0.0000, 0.0008])
	Low	High	−0.01*	−0.0245	−0.006	
	Medium	Low	−0.02*	−0.0363	−0.0091	
	Medium	High	−0.02*	−0.0269	−0.0066	Indices of conditional moderated mediation for low product criticality = −0.0538 (95% CI = [−0.0861, −0.0219]) and for high product criticality = −0.0390 (95% CI = [−0.0636, −0.0158])
	High	Low	−0.02*	−0.0391	−0.0098	
	High	High	−0.02*	−0.0289	−0.007	
PTR → WB	Low	Low	$.00^{ns}$	−0.0004	0.0031	Index of moderated mediation for environmental concerns = 0.0003 (95% CI = [0.0000, 0.0007])
	Low	High	$.00^{ns}$	−0.0003	0.0023	
	Medium	Low	$-.00^{ns}$	−0.0022	0.0006	
	Medium	High	$-.00^{ns}$	−0.0016	0.0005	Indices of conditional moderated mediation for low product criticality = 0.0387 (95% CI = [0.0108, 0.0667]) and for high product criticality = 0.0280 (95% CI = [0.0079, 0.0496])
	High	Low	−0.00*	−0.0047	−0.0002	
	High	High	−0.00*	−0.0034	−0.0001	
PC → WB	Low	Low	−0.00*	−0.0082	−0.0019	Index of moderated mediation for environmental concerns = −0.0005 (95% CI = [−0.0011, −0.0001])
	Low	High	−0.00*	−0.0061	−0.0014	
	Medium	Low	$-.00^{ns}$	−0.0034	0.0002	
	Medium	High	$-.00^{ns}$	−0.0025	0.0001	Indices of conditional moderated mediation for low product criticality = 0.0556 (95% CI = [0.0284, 0.0845]) and for high product criticality = 0.0403 (95% CI = [0.0199, 0.0629])
	High	Low	$.00^{ns}$	−0.0012	0.0037	
	High	High	$.00^{ns}$	−0.0009	0.0027	

* *Notes*. $p < .05$, ns: non-significant, PE: performance expectancy, PTR: perceived technology risk, PC: privacy concerns, WB: well-being.

moderated mediation effects were positive, with a slightly stronger effect observed for low product criticality (0.0387, 95% CI = [0.0108, 0.0667]) compared to high product criticality (0.0280, 95% CI = [0.0079, 0.0496]).

Lastly, for the pathway via privacy concerns and well-being, the index of moderated mediation for environmental concerns was negative at −0.0005 (95% CI = [−0.0011, −0.0001]), indicating a small but significant effect in the opposite direction. The conditional moderated mediation effects were positive, with a stronger effect for low product criticality (0.0556, 95% CI = [0.0284, 0.0845]) than for high product criticality (0.0403, 95% CI = [0.0199, 0.0629]).

6. Discussion of the results

Our study contributes new insights to the existing body of literature on AI-automated delivery drones by examining how environmental concerns, product criticality, and risks related to physical accidents and cyberattacks influence consumer adoption and behavioral intentions. These findings enhance, refine, and in some instances, challenge existing research across these domains.

Building on the work of Hwang and Kim (2019), our research underscores the role that environmental concerns play in shaping consumer attitudes toward AI-automated delivery drones. While Hwang and Kim highlighted how a strong green image can boost consumer intentions to adopt AI-automated drone technology, our findings take this further by showing that environmental concerns positively moderate the relationship between performance expectancy, social influence, and well-being. This suggests that users who prioritize environmental sustainability experience greater emotional and psychological benefits from AI-automated drone use, aligning with the findings of Manfreda et al. (2019) on the environmental advantages of AI-automated drones, such as reduced energy consumption and lower CO2 emissions. However, our study also reveals a more nuanced interaction between environmental concerns and perceived risks, particularly privacy concerns. Contrary to previous research by Khan et al. (2019) and Jiang et al. (2023), which suggested that environmental and privacy concerns generally align, we found that higher environmental concerns unexpectedly reduce the negative impact of privacy concerns on well-being. This unexpected buffering effect challenges the assumption that these concerns always reinforce each other, indicating a more complex dynamic that warrants further exploration. This counterintuitive result may be explained by moral licensing mechanisms (Simbrunner and Schlegelmilch, 2017), whereby engaging in environmentally responsible behavior provides individuals with a sense of moral credit, which they can then "spend" by accepting ethically questionable trade-offs, such as diminished privacy. Similar effects have been observed by Mazar and Zhong (2010), who found that purchasing green products can paradoxically increase unethical behavior like theft. In our context, the mechanism does not involve an active transgression, but rather a greater tolerance for risk: users become less motivated to resist potential privacy threats because the technology serves a higher environmental purpose. This aligns with broader findings in consumer self-regulation research, which highlight that perceived goal progress (e.g., contributing to environmental good) can reduce subsequent self-control efforts, particularly when trade-offs involve non-moralized domains such as privacy (Elena Francke and Carrete, 2023).

Regarding product criticality, our study offers a novel contribution by showing that it significantly influences the relationship between well-being and behavioral intention to use AI-automated delivery drones. While previous research by Hagtvedt and Patrick (2009) and Zaichkowsky (1985) focused on the role of product importance in consumer decision-making, our findings extend this by demonstrating that when the criticality of the product being delivered is high, such as with medical supplies, the positive effect of well-being on the intention to use AI-automated drones is diminished. This contrasts with studies by Holzmann et al. (2021) and Lim et al. (2024), which highlighted the central role of performance expectancy and task-technology fit in adoption decisions. Our research suggests that the perceived importance of the product can override the emotional benefits associated with AI-automated drone use, offering a more nuanced understanding of consumer behavior, particularly in the context of essential goods.

Our investigation into the effects of physical accidents and cyberattacks further contributes to the literature by examining their impact on perceived technology risks and performance expectancy. Prior studies by Luppicini and So (2016) and Ravich (2017) have documented public concerns about the safety and security of AI-automated drone technology. Our findings support these concerns, showing that physical accidents significantly increase perceived technology risks and decrease performance expectancy, which in turn, reduces the likelihood of adopting the technology. This extends the work of Koopman and Wagner (2017) and Mathew et al. (2021) by providing empirical evidence of how these risks influence consumer perceptions. Additionally, our study aligns with research by Martins et al. (2014) and Choe et al. (2021) on the impact of cyberattacks, demonstrating that security breaches not only heighten perceived risks but also negatively affect performance expectancy and privacy concerns. These findings emphasize the importance of addressing cybersecurity and encourage the adoption of AI-automated delivery drones, thereby expanding the existing literature by quantifying the effects of these risks in this specific context.

7. Contributions

7.1. Theoretical contributions

A first key theoretical contribution of this research lies in its advancement of the AI-automated delivery drone acceptance literature through a theoretically enriched application of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh and Thong, 2012). While prior work has primarily emphasized the direct effects of perceived usefulness and social influence on behavioral intention (Kapser and Abdelrahman, 2020; Holzmann et al., 2021), our study extends this model by incorporating affective mechanisms and contextual moderators that are particularly relevant for emotionally and ethically charged technologies like autonomous delivery systems.

A central theoretical innovation is the integration of user well-being as a mediating variable between both perceived benefits (performance expectancy and social influence) and perceived risks (technological and privacy-related), and behavioral intention. This construct is grounded in theories of hedonic well-being (which emphasizes emotional comfort and the avoidance of distress) and eudaimonic well-being, which centers on psychological functioning, autonomy, and competence (Ryan and Deci, 2001; Ryff, 1989). Drawing from transformative consumer research (Davis and Pechmann, 2013; Chitturi et al., 2008), our study shows that individuals are more likely to adopt a technology not merely because it is useful or socially valued, but because it contributes to a positive emotional and psychological state. In doing so, we move beyond traditional utility-based models by foregrounding the affective foundations of technology adoption.

Moreover, by examining both perceived benefits and risks simultaneously, and modeling their direct and indirect effects through well-being, our study builds upon and extends perceived risk theory (Featherman and Pavlou, 2003; Forsythe and Shi, 2003) and privacy calculus theory (Hong and Thong, 2013). We demonstrate that emotional responses to functional, physical, and privacy-related risks play a critical role in shaping the user experience, revealing a more complex and psychologically grounded understanding of adoption behavior.

The model also introduces two moderating variables that contribute to the explanatory richness of our framework. First, environmental concern, conceptualized as a value-based orientation toward ecological sustainability (Hwang and Kim, 2019; Hartmann and Apaolaza-Ibáñez, 2012), significantly amplifies the positive effects of perceived benefits on well-being and weakens the negative effects of privacy concerns. This unexpected attenuation of privacy-related anxiety can be interpreted through the lens of moral licensing theory (Mazar and Zhong, 2010; Monin and Miller, 2001). According to this perspective, individuals who engage in or endorse morally virtuous behaviors, such as supporting sustainable technologies, may feel psychologically licensed to tolerate ethically questionable trade-offs, such as diminished personal privacy. In this context, environmental concern appears to act as a moral buffer, allowing individuals to uphold their positive self-image while accepting risks they might otherwise reject. This insight expands the application of moral licensing theory into the realm of sustainable technology adoption and highlights how moral self-perception can influence emotional responses to technological risk.

Second, we introduce product criticality (e.g., delivery of medical vs. retail items) as a contextual moderator. Our results show that when the stakes of delivery are perceived as high, the positive influence of well-being on behavioral intention is weakened. This suggests that instrumental concerns, such as speed, reliability, and safety, may override affective evaluations in critical usage contexts, offering new insight into boundary conditions for affect-driven adoption models.

These contributions deepen the explanatory power of UTAUT2 and bridge it with theoretical perspectives from transformative consumer research, well-being theory, perceived risk and privacy calculus, and green consumption. By integrating cognitive, affective, and value-based dimensions, our model offers a more holistic account of how users assess emotionally and morally salient innovations like AI-automated drone delivery.

7.2. Managerial contributions

To stay competitive amid rising labor costs, urban congestion, and post-pandemic challenges, logistics firms are turning to AI-automated drone-based delivery for its cost efficiency, speed, and contactless service. Key adoption drivers (e.g., performance expectancy and social influence) should be highlighted through clear communication of functional benefits such as traffic-free routing, urgency handling, and reduced delivery times (Holzmann et al., 2021; Kapser and Abdelrahman, 2020).

Investments in AI-automated drone infrastructure can further enhance reliability and customer satisfaction. Firms should also promote AI-automated drones' environmental advantages such as lower CO_2 emissions and noise pollution, to strengthen identity-aligned consumer values and well-being (Figliozzi, 2017; Goodchild and Toy, 2018; Park et al., 2018; Stolaroff et al., 2018).

However, concerns over safety and privacy remain significant barriers (Nentwich and Horváth, 2018; Schenkelberg, 2016). Managers should be aware that moral licensing may cause consumers to overlook privacy risks when services are framed as eco-friendly. Thus, sustainability messaging should be paired with transparent privacy protections to maintain trust (Mazar and Zhong, 2010). Communicating safety data, emphasizing protective features, and providing user support, such as secure drop-off systems, are essential to address risk perceptions and improve acceptance.

7.3. Policy contributions

While managerial initiatives are essential, policy support is crucial for the safe, sustainable, and socially accepted integration of AI-automated drones into urban logistics. Policymakers must address moral licensing, which may lead consumers to downplay privacy risks in green technologies such as AI-automated drones. Clear regulatory frameworks should enforce privacy-by-design and transparent data disclosures, while public education must reinforce that environmental benefits should not override digital rights (Mazar and Zhong, 2010).

Governments should standardize AI-automated drone safety protocols (e.g., flight corridors, landing zones, and fail-safes) and fund pilot programs to evaluate usability and public acceptance in varied contexts. Guidelines for transparent communication about AI-automated drone use, privacy, and safety can help mitigate public concern.

Environmental incentives (e.g., tax benefits for low-emission tech) and inclusion of AI-automated drones in urban mobility plans will further encourage sustainable adoption. Lastly, investing in shared smart infrastructure like landing pads and docking hubs can reduce private costs, promote interoperability, and ensure equitable access.

8. Limitations and future research directions

Despite its contributions, this study has several limitations that offer valuable opportunities for future research. First, the sample composition may limit the generalizability of the findings. As the participants were exclusively drawn from France, cultural, infrastructural, and regulatory differences in other countries, particularly those with more advanced or less developed AI-automated drone ecosystems, were not captured. Moreover, the sample was skewed toward urban and suburban residents, potentially underrepresenting perspectives from rural populations who may experience different logistical needs, technological readiness, or infrastructure constraints. Our study focuses on Generation Z, a tech-savvy cohort widely used in technology adoption research for comparability. While not representative of the entire population, Gen Z constitutes a relevant market segment for AI-automated delivery drones and they are typically more tech-savvy and thus more open to AI-automated drones (Barbosa et al., 2019; Mcmillan and Morrison, 2006). Future research should incorporate more representative and cross-cultural comparisons with samples from diverse socio-demographic and geographical contexts.

Second, participants evaluated AI-automated drone delivery services based on a brief hypothetical scenario, without any direct experience or interaction with the technology. This limitation may have introduced hypothetical bias and limited the ecological validity of user perceptions. To overcome this, future studies should adopt experimental or experiential designs, including field experiments, prototypes, or virtual reality simulations to expose participants to more realistic and emotionally salient interactions with AI-automated drone systems. These methods could enhance users' understanding of the technology and provide richer insights into trust formation, usability perception, and behavioral intention.

Third, while our model incorporates key predictors of AI-automated drone delivery adoption, several theoretical and conceptual gaps remain. The study's treatment of well-being was limited to a general affective appraisal, potentially overlooking other critical dimensions such as psychological security, physical safety, social connectivity, or financial stress relief. Future research should adopt a multidimensional conceptualization of well-being, distinguishing between hedonic, eudaimonic, and psychological components to capture more nuanced consumer responses. Additionally, there is a need for deeper exploration of the social, ethical, and regulatory implications of AI-automated drone use, such as equity in access, surveillance concerns, noise pollution, and airspace governance, which may significantly affect public acceptance and societal trust in AI-automated drone-based services.

Fourth, while our study distinguishes between urban and non-urban contexts, the available data did not permit a more fine-grained geographical analysis that could capture intra-urban variation or the distinct socio-spatial dynamics of specific cities or neighborhoods (Li and Dang, 2024; Li and Kim, 2022). Specifically, we were unable to control for or segment the sample by finer geographic units such as city size, population density, or specific regions. We recognize that such stratification could clarify whether the observed relationships are robust across different local contexts or are disproportionately driven by particular areas. Future research should therefore incorporate more detailed locational data to enable comparative analyses across diverse settings and to explore how contextual factors, such as infrastructure, local policy environments, and population density, shape risk perceptions, environmental attitudes, and technology adoption behaviors. Such granularity would offer a more nuanced understanding of spatial heterogeneity in public acceptance of AI-automated drone deliveries.

Finally, future studies should directly investigate how moral licensing affects consumer acceptance of ethical compromises, such as diminished privacy. Research should explore who is most susceptible to moral licensing and whether its effects persist over time. This will clarify how moral licensing shapes long-term attitudes toward sustainable but intrusive technologies.

CRediT authorship contribution statement

Lars Meyer-Waarden: Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Julien Cloarec:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Stéphane Salgado:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Vincent Favarin:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization.

Data availability

Data will be made available on request.

References

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Amazon, 2025. https://www.aboutamazon.com/news/transportation/amazon-drone-deliver-package.

Ayadi, N., Paraschiv, C., Vernette, E., 2017. Increasing consumer well-being : risk as potential driver of happiness. Appl. Econ. 49 (43), 4321–4335. https://doi.org/10.1080/00036846.2017.1282142.

Bandura, A., 1989. Human agency in social cognitive theory. Am. Psychol. 44 (9), 1175–1184. https://doi.org/10.1037/0003-066X.44.9.1175.

Cacioppo, J.T., Petty, R.E., Kao, C.F., Rodriguez, R., 1986. Central and peripheral routes to persuasion : an individual difference perspective. J. Pers. Soc. Psychol. 51 (5), 1032–1043. https://doi.org/10.1037/0022-3514.51.5.1032.

Chang, C., 2011. Feeling ambivalent about going green. J. Advert. 40 (4), 19–32. https://doi.org/10.2753/JOA0091-3367400402.

Chen, H., Hu, Z., Solak, S., 2021. Improved delivery policies for future drone-based delivery systems. Eur. J. Oper. Res. 294 (3), 1181–1201. https://doi.org/10.1016/j.ejor.2021.02.039.

Chen, X., Ulmer, M.W., Thomas, B.W., 2022. Deep Q-learning for same-day delivery with vehicles and drones. Eur. J. Oper. Res. 298 (3), 939–952. https://doi.org/10.1016/j.ejor.2021.06.021.

Chiang, W.-C., Li, Y., Shang, J., Urban, T.L., 2019. Impact of drone delivery on sustainability and cost : realizing the UAV potential through vehicle routing optimization. Appl. Energy 242, 1164–1175. https://doi.org/10.1016/j.apenergy.2019.03.117.

Chitturi, R., Raghunathan, R., Mahajan, V., 2008. Delight by design : the role of hedonic versus utilitarian benefits. J. Mark. 72 (3), 48–63. https://doi.org/10.1509/jmkg.72.3.48.

Choe, J.Y. (Jacey), Kim, J.J., Hwang, J., 2021. Perceived risks from drone food delivery services before and after COVID-19. Int. J. Contemp. Hosp. Manag. 33 (4), 1276–1296. https://doi.org/10.1108/IJCHM-08-2020-0839.

Cox, D.F., Rich, S.U., 1964. Perceived risk and consumer decision-making—the case of telephone shopping. J. Mark. Res. 1 (4), 32–39. https://doi.org/10.1177/002224376400100405.

Davis, B., Pechmann, C., 2013. Introduction to the special issue on transformative consumer research : developing theory to mobilize efforts that improve consumer and societal well-being. J. Bus. Res. 66 (8), 1168–1170. https://doi.org/10.1016/j.jbusres.2012.08.008.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13 (3), 319. https://doi.org/10.2307/249008.

Dhar, R., Wertenbroch, K., 2000. Consumer choice between hedonic and utilitarian goods. J. Mark. Res. 37 (1), 60–71. https://doi.org/10.1509/jmkr.37.1.60.18718.

Diener, E., 1984. Subjective well-being. Psychol. Bull. 95 (3), 542–575. https://doi.org/10.1037/0033-2909.95.3.542.

Diener, E., Chan, M.Y., 2011. Happy people live longer : subjective well-being contributes to health and longevity. Appl. Psychol. Health Well Being 3 (1), 1–43. https://doi.org/10.1111/j.1758-0854.2010.01045.x.

Diener, E., Oishi, S., Tay, L., 2018. Advances in subjective well-being research. Nat. Hum. Behav. 2 (4), 253–260. https://doi.org/10.1038/s41562-018-0307-6.

DoorDash, 2025. https://about.doordash.com/en-us/news/doordash-wing-expand-to-charlotte.

Elena Francke, A., Carrete, L., 2023. Consumer self-regulation : looking back to look forward. A systematic literature review. J. Bus. Res. 157, 113461. https://doi.org/10.1016/j.jbusres.2022.113461.

Featherman, M.S., Pavlou, P.A., 2003. Predicting e-services adoption : a perceived risk facets perspective. International Journal of Human-Computer Studies 59 (4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3.

Festinger, L., 1954. A theory of social comparison processes. Hum. Relat. 7 (2), 117–140. https://doi.org/10.1177/001872675400700202.

Figliozzi, M.A., 2017. Lifecycle modeling and assessment of unmanned aerial vehicles (drones) CO_2e emissions. Transp. Res. Part D: Transp. Environ. 57, 251–261. https://doi.org/10.1016/j.trd.2017.09.011.

Forsythe, S.M., Shi, B., 2003. Consumer patronage and risk perceptions in internet shopping. J. Bus. Res. 56 (11), 867–875. https://doi.org/10.1016/S0148-2963(01)00273-9.

Gao, L., Bai, X., 2014. A unified perspective on the factors influencing consumer acceptance of internet of things technology. Asia Pac. J. Mark. Logist. 26 (2), 211–231. https://doi.org/10.1108/APJML-06-2013-0061.

Gefen, D., Straub, D.W., 2004. Consumer trust in B2C e-commerce and the importance of social presence : experiments in e-products and e-services. Omega 32 (6), 407–424. https://doi.org/10.1016/j.omega.2004.01.006.

Goodchild, A., Toy, J., 2018. Delivery by drone : an evaluation of unmanned aerial vehicle technology in reducing CO_2 emissions in the delivery service industry.

Transp. Res. Part D: Transp. Environ. 61, 58–67. https://doi.org/10.1016/j.trd.2017.02.017.

Gurumurthy, K.M., Kockelman, K.M., 2020. Modeling Americans' autonomous vehicle preferences : A focus on dynamic ride-sharing, privacy & long-distance mode choices. Technol. Forecast. Soc. Change 150, 119792. https://doi.org/10.1016/j.techfore.2019.119792.

Hagtvedt, H., Patrick, V.M., 2009. The broad embrace of luxury : hedonic potential as a driver of brand extendibility. J. Consum. Psychol. 19 (4), 608–618. https://doi.org/10.1016/j.jcps.2009.05.007.

Harman, D., 1967. A single factor test of common method variance. J. Psychol. Theol. 35 (1967), 359–378.

Hartmann, P., Apaolaza-Ibáñez, V., 2012. Consumer attitude and purchase intention toward green energy brands : the roles of psychological benefits and environmental concern. J. Bus. Res. 65 (9), 1254–1263. https://doi.org/10.1016/j.jbusres.2011.11.001.

Hayes, A.F., 2021. Introduction to Mediation, Moderation, and Conditional Process Analysis, 3rd Ed. Guilford Press. In: http://afhayes.com/introduction-to-mediation-moderation-and-conditional-process-analysis.html.

Holzmann, P., Wankmüller, C., Globocnik, D., Schwarz, E.J., 2021. Drones to the rescue ? Exploring rescue workers' behavioral intention to adopt drones in mountain rescue missions. Int. J. Phys. Distrib. Logist. Manag. 51 (4), 381–402. https://doi.org/10.1108/IJPDLM-01-2020-0025.

Hong, W., Thong, J.Y., 2013. Internet privacy concerns : an integrated conceptualization and four empirical studies. MIS Q. 37 (1), 275–298.

Huta, V., Ryan, R.M., 2010. Pursuing pleasure or virtue : the differential and overlapping well-being benefits of hedonic and Eudaimonic motives. J. Happiness Stud. 11 (6), 735–762. https://doi.org/10.1007/s10902-009-9171-4.

Hwang, J., Cho, S.-B., Kim, W., 2019. Consequences of psychological benefits of using eco-friendly services in the context of drone food delivery services. J. Travel Tour. Mark. 36 (7), 835–846. https://doi.org/10.1080/10548408.2019.1586619.

Hwang, J., Choe, J.Y. (Jacey), 2019. Exploring perceived risk in building successful drone food delivery services. Int. J. Contemp. Hosp. Manag. https://doi.org/10.1108/IJCHM-07-2018-0558 ahead-of-p(ahead-of-print).

Hwang, J., Kim, H., 2019. Consequences of a green image of drone food delivery services : the moderating role of gender and age. Bus. Strateg. Environ. 28 (5), 872–884. https://doi.org/10.1002/bse.2289.

Jiang, Y., Lai, P.-L., Yang, C.-C., Wang, X., 2023. Exploring the factors that drive consumers to use contactless delivery services in the context of the continued COVID-19 pandemic. J. Retail. Consum. Serv. 72, 103276. https://doi.org/10.1016/j.jretconser.2023.103276.

Kapser, S., Abdelrahman, M., 2020. Acceptance of autonomous delivery vehicles for last-mile delivery in Germany – extending UTAUT2 with risk perceptions. Transportation Research Part C: Emerging Technologies 111, 210–225. https://doi.org/10.1016/j.trc.2019.12.016.

Khan, R., Tausif, S., Malik, A.J., 2019. Consumer acceptance of delivery drones in urban areas. Int. J. Consum. Stud. 43 (1), 87–101. https://doi.org/10.1111/ijcs.12487.

King, W.R., He, J., 2006. A meta-analysis of the technology acceptance model. Inf. Manag. 43 (6), 740–755. https://doi.org/10.1016/j.im.2006.05.003.

Kinnear, T.C., Taylor, J.R., Ahmed, S.A., 1974. Ecologically concerned consumers : who are they? J. Mark. 38 (2), 20. https://doi.org/10.2307/1250192.

Koh, L.Y., Lee, J.Y., Wang, X., Yuen, K.F., 2023. Urban drone adoption : addressing technological, privacy and task–technology fit concerns. Technol. Soc. 72, 102203. https://doi.org/10.1016/j.techsoc.2023.102203.

Koopman, P., Wagner, M., 2017. Autonomous vehicle safety : an interdisciplinary challenge. IEEE Intell. Transp. Syst. Mag. 9 (1), 90–96. https://doi.org/10.1109/MITS.2016.2583491.

Leon, S., Chen, C., Ratcliffe, A., 2021. Consumers' perceptions of last mile drone delivery. Int J Log Res Appl 26 (3), 345–364. https://doi.org/10.1080/13675567.2021.1957803.

Li, X., Dang, A., 2024. Spatial patterns of drone adoption: insights from communities in Southern California. Technol. Forecast. Soc. Chang. 203, 123391.

Li, X., Kim, J.H., 2022. Managing disruptive technologies: exploring the patterns of local drone policy adoption in California. Cities 126, 103736.

Lim, X.-J., Chang, J.Y.-S., Cheah, J.-H., Lim, W.M., Kraus, S., Dabić, M., 2024. Out of the way, human ! Understanding post-adoption of last-mile delivery robots. Technol. Forecast. Soc. Chang. 201, 123242. https://doi.org/10.1016/j.techfore.2024.123242.

Luppicini, R., So, A., 2016. A technoethical review of commercial drone use in the context of governance, ethics, and privacy. Technol. Soc. 46, 109–119. https://doi.org/10.1016/j.techsoc.2016.03.003.

Mahmoodi, A., Hashemi, L., Laliberte, J., Millar, R.C., Walter Meyer, R., 2024. Revolutionizing RPAS logistics and reducing CO2 emissions with advanced RPAS technology for delivery systems. Cleaner Logistics and Supply Chain 12, 100166. https://doi.org/10.1016/j.clscn.2024.100166.

Mahmoud, A.B., Mahroof, K., 2025. The proof is in the pudding : public beliefs, emotions and sentiments on drone deliveries in extreme contexts. Eur. J. Mark. https://doi.org/10.1108/ejm-08-2024-0631.

Mainieri, T., Barnett, E.G., Valdero, T.R., Unipan, J.B., Oskamp, S., 1997. Green buying : the influence of environmental concern on consumer behavior. J. Soc. Psychol. 137 (2), 189–204. https://doi.org/10.1080/00224549709595430.

Malhotra, N.K., Kim, S.S., Agarwal, J., 2004. Internet users' information privacy concerns (IUIPC): the construct, the scale, and a causal model. Inf. Syst. Res. 15 (4), 336–355. https://doi.org/10.1287/isre.1040.0032.

Manfreda, S., Dvorak, P., Mullerova, J., Herban, S., Vuono, P., Justel, J.A., Perks, M., 2019. Assessing the accuracy of digital surface models derived from optical imagery acquired with unmanned aerial systems. Drones 3 (1), 15. https://doi.org/10.3390/drones3010015.

Markets and Markets, 2024. https://www.marketsandmarkets.com/Market-Reports/unmanned-aerial-vehicles-uav-market-662.html.

Martins, C., Oliveira, T., Popovič, A., 2014. Understanding the internet banking adoption : a unified theory of acceptance and use of technology and perceived risk application. Int. J. Inf. Manag. 34 (1), 1–13. https://doi.org/10.1016/j.ijinfomgt.2013.06.002.

Mathew, A.O., Jha, A.N., Lingappa, A.K., Sinha, P., 2021. Attitude towards drone food delivery services—role of innovativeness, perceived risk, and green image. J. Open Innov.: Technol. Mark. Complex. 7 (2), 144. https://doi.org/10.3390/joitmc7020144.

Mazar, N., Zhong, C.-B., 2010. Do green products make us better people? Psychol. Sci. 21 (4), 494–498. https://doi.org/10.1177/0956797610363538.

Mcmillan, S.J., Morrison, M., 2006. Coming of age with the internet : a qualitative exploration of how the internet has become an integral part of young people's lives. New Media Soc. 8 (1), 73–95. https://doi.org/10.1177/1461444806059871.

Meuter, M.L., Bitner, M.J., Ostrom, A.L., Brown, S.W., 2005. Choosing among alternative service delivery modes : an investigation of customer trial of self-service technologies. J. Mark. 69 (2), 61–83. https://doi.org/10.1509/jmkg.69.2.61.60759.

Meyer-Waarden, L., Cloarec, J., 2022. "Baby, you can drive my car": psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. Technovation 109, 102348.

Meyer-Waarden, L., Cloarec, J., Adams, C., Aliman, D.N., Wirth, V., 2021. Home, sweet home : how well-being shapes the adoption of artificial intelligence-powered apartments in smart cities. Systèmes d'information & management 26 (4), 55–88. https://doi.org/10.3917/sim.214.0055.

Monin, B., Miller, D.T., 2001. Moral credentials and the expression of prejudice. J. Pers. Soc. Psychol. 81 (1), 33–43. https://doi.org/10.1037/0022-3514.81.1.33.

Moshagen, M., Bader, M., 2024. semPower : power analyses for SEM (version 2.1.1) [Logiciel]. https://cran.r-project.org/web/packages/semPower/index.html.

Moshagen, M., Erdfelder, E., 2016. A new strategy for testing structural equation models. Struct. Equ. Model. Multidiscip. J. 23 (1), 54–60. https://doi.org/10.1080/10705511.2014.950896.

Nentwich, M., Horváth, D.M., 2018. Vision Lieferdrohnen. TATuP - Zeitschrift für Technikfolgenabschätzung in Theorie und Praxis 27 (2), 46–52. https://doi.org/10.14512/tatup.27.2.46.

Osakwe, C.N., Hudik, M., Říha, D., Stros, M., Ramayah, T., 2022. Critical factors characterizing consumers' intentions to use drones for last-mile delivery : does delivery risk matter? J. Retail. Consum. Serv. 65, 102865. https://doi.org/10.1016/j.jretconser.2021.102865.

Pande, D., Taeihagh, A., 2021. Investigating user acceptance of autonomous systems : A Singapore perspective on governance using a modified UTAUT. In: 5th International Conference on Public Policy (ICPP5), pp. 1–26.

Park, J., Kim, S., Suh, K., 2018. A comparative analysis of the environmental benefits of drone-based delivery services in Urban and rural areas. Sustainability 10 (3), 888. https://doi.org/10.3390/su10030888.

Phelps, J., Nowak, G., Ferrell, E., 2000. Privacy concerns and consumer willingness to provide personal information. J. Public Policy Mark. 19 (1), 27–41. https://doi.org/10.1509/jppm.19.1.27.16941.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research : a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879.

Ramadan, Z.B., Farah, M.F., Mrad, M., 2017. An adapted TPB approach to consumers' acceptance of service-delivery drones. Tech. Anal. Strat. Manag. 29 (7), 817–828. https://doi.org/10.1080/09537325.2016.1242720.

Ravich, T.M., 2017. Evolving law on airport implications by unmanned aerial systems. Transp. Res. Board. https://doi.org/10.17226/24932.

Reid, D., 2016. Domino's delivers world's first ever pizza by drone. https://www.cnbc.com/2016/11/16/dominos-has-delivered-the-worlds-first-ever-pizza-by-drone-to-a-new-zealand-couple.html.

Rozanski, A., Kubzansky, L.D., 2005. Psychologic functioning and physical health : a paradigm of flexibility. Psychosom. Med. 67, S47–S53. https://doi.org/10.1097/01.psy.0000164253.69550.49.

Ryan, R.M., Deci, E.L., 2001. On happiness and human potentials : a review of research on hedonic and Eudaimonic well-being. Annu. Rev. Psychol. 52 (1), 141–166. https://doi.org/10.1146/annurev.psych.52.1.141.

Ryff, C.D., 1989. Happiness is everything, or is it? Explorations on the meaning of psychological well-being. J. Pers. Soc. Psychol. 57 (6), 1069–1081. https://doi.org/10.1037/0022-3514.57.6.1069.

Sah, B., Gupta, R., Bani-Hani, D., 2021. Analysis of barriers to implement drone logistics. Int J Log Res Appl 24 (6), 531–550. https://doi.org/10.1080/13675567.2020.1782862.

Schenkelberg, F., 2016. How reliable does a delivery drone have to be? Annual Reliability and Maintainability Symposium (RAMS) 2016, 1–5. https://doi.org/10.1109/RAMS.2016.7448054.

Schmidt, S., Saraceni, A., 2024. Consumer acceptance of drone-based technology for last mile delivery. Res. Transp. Econ. 103, 101404. https://doi.org/10.1016/j.retrec.2023.101404.

Schutter, L.D., 2021. Conmet : construct measurement evaluation tool (version 0.1.0) [Logiciel]. https://cran.r-project.org/web/packages/conmet/index.html.

Schwela, D., Zali, O., 2020. Motor vehicles and air pollution. In: Urban Traffic Pollution. https://doi.org/10.1201/9781482272093-8.

Shadish, W.R., Cook, T.D., Campbell, D.T., 2001. Experimental and Quasi-Experimental Designs for Generalized Causal Inference. Houghton Mifflin.

Shahzad, M.F., Yuan, J., Shahzad, K., 2024. Elevating culinary skies : unveiling hygiene motivations, environmental trust, and market performance in drone food delivery adoption in China. Technol. Forecast. Soc. Chang. 203, 123375. https://doi.org/10.1016/j.techfore.2024.123375.

Sham, R., Chong, H.X., Cheng-Xi Aw, E., Bibi Tkm Thangal, T., Abdamia, N.B., 2023. Switching up the delivery game : understanding switching intention to retail drone delivery services. J. Retail. Consum. Serv. 75, 103478. https://doi.org/10.1016/j.jretconser.2023.103478.

Simbrunner, P., Schlegelmilch, B.B., 2017. Moral licensing : a culture-moderated meta-analysis. Management Review Quarterly 67 (4), 201–225. https://doi.org/10.1007/s11301-017-0128-0.

Soni, M., Jain, K., Jajodia, I., 2021. Mobile health (mHealth) application loyalty in young consumers. Young Consum. 22 (3), 429–455. https://doi.org/10.1108/yc-10-2020-1236.

Stern, P.C., 1992. Psychological dimensions of global environmental change. Annu. Rev. Psychol. 43 (1), 269–302. https://doi.org/10.1146/annurev.ps.43.020192.001413.

Stolaroff, J.K., Samaras, C., O'Neill, E.R., Lubers, A., Mitchell, A.S., Ceperley, D., 2018. Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery. Nat. Commun. 9 (1), 409. https://doi.org/10.1038/s41467-017-02411-5.

Su, R., Tay, L., Diener, E., 2014. The development and validation of the comprehensive inventory of thriving (CIT) and the brief inventory of thriving (BIT). Appl. Psychol. Health Well Being 6 (3), 251–279. https://doi.org/10.1111/aphw.12027.

Sweeney, J.C., Soutar, G.N., 2001. Consumer perceived value : the development of a multiple item scale. J. Retail. 77 (2), 203–220. https://doi.org/10.1016/S0022-4359(01)00041-0.

Venkatesh, Thong, Xu, 2012. Consumer acceptance and use of information technology : extending the unified theory of acceptance and use of technology. MIS Q. 36 (1), 157. https://doi.org/10.2307/41410412.

Venkatesh, V., Thong, J., Hong Kong University of Science and Technology, Xu, X., The Hong Kong Polytechnic University, 2016. Unified theory of acceptance and use of technology : a synthesis and the road ahead. J. Assoc. Inf. Syst. 17 (5), 328–376. https://doi.org/10.17705/1jais.00428.

Voss, K.E., Spangenberg, E.R., Grohmann, B., 2003. Measuring the hedonic and utilitarian dimensions of consumer attitude. J. Mark. Res. 40 (3), 310–320. https://doi.org/10.1509/jmkr.40.3.310.19238.

Walmart, 2025. https://corporate.walmart.com/news/2025/06/05/walmart-takes-flight-with-drone-delivery-expansion-to-5-new-cities-redefining-fast-flexible-retail.

Yoo, W., Yu, E., Jung, J., 2018. Drone delivery : factors affecting the public's attitude and intention to adopt. Telematics Inform. 35 (6), 1687–1700. https://doi.org/10.1016/j.tele.2018.04.014.

Zaichkowsky, J.L., 1985. Measuring the involvement construct. J. Consum. Res. 12 (3), 341. https://doi.org/10.1086/208520.

Zhong, J.Y., Mitchell, V., 2012. Does consumer well-being affect hedonic consumption? Psychol. Mark. 29 (8), 583–594. https://doi.org/10.1002/mar.20545.

Lars Meyer-Waarden is a Full Professor of Marketing at the Toulouse School of Management (University of Toulouse Capitole). His research explores how AI big data, and smart digital technologies reshape customer relationships, user experience, and well-being in smart cities and autonomous mobility ecosystems. Positioned at the intersection of CRM, data-driven marketing, and digital innovation, his work examines technologies such as AI, IoT, smart connected ecosystems, with a particular focus on trust, privacy, ethical decision-making, and human-centered well-being. He also serves as an Adjunct Professor at Chulalongkorn Business School (Thailand) and at the Lee Shau Kee School of Business and Administration, Hong Kong Metropolitan University. He is the Director of the Chair "Smart City & Urban Experience for Well-Being." He is the author of several books on customer loyalty/loyalty programs and has published extensively in leading international academic journals, including *Journal of the Academy of Marketing Science, Journal of Retailing, Tourism Management, Information & Management, Journal of Interactive Marketing, European Journal of Marketing, Journal of Service Marketing, Journal of Business Research, Technological Forecasting and Social Change, Journal of Retailing and Consumer Services, International Journal of Electronic Commerce*.

Julien Cloarec is a Full Professor of Quantitative Marketing at iaelyon School of Management, Université Jean Moulin Lyon 3, France. An internationally recognized expert in artificial intelligence, his work focuses on ensuring that AI can be deployed without compromising user privacy. He collaborates with regulatory bodies, professional associations, and academic institutions to raise awareness, influence policy, and promote responsible AI development that balances innovation with privacy protection. His research has been published in journals such as *Research Policy, Technological Forecasting and Social Change, Technovation, Journal of Business Research, Psychology & Marketing, and Transportation Research Part A*.

Stéphane Salgado is an Associate Professor in the Marketing Department at Toulouse School of Management (Université Toulouse Capitole, France). He received his PhD from the Aix-en-Provence Graduate School of Management (Aix-Marseille Université, France). During and after his doctoral studies, he worked as a lecturer at Arts et Métiers ParisTech. His research focuses on creativity, open innovation contests, rewards, and user innovation. His work has been published in international journals such as *Technological Forecasting and Social Change, Journal of Business Research, and Journal of Travel Research, Technology in Society*.

Vincent Favarin is an Assistant Professor of Marketing at IAE Clermont Auvergne School of Management, Université Clermont Auvergne. His research focuses on the transformative privacy calculus and its impact on consumer adoption of AI-powered services. By examining how individuals weigh the benefits and risks of sharing personal data, his work seeks to deepen understanding of the factors influencing the acceptance and use of artificial intelligence in everyday services.