

GENERATIONAL RESEARCH ON TECHNOLOGY ACCEPTANCE AND USE: WHAT'S POPULAR ISN'T ALWAYS RIGHT

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Generations are a popular tool used by practitioners and researchers to divide consumers into groups that purportedly share values and characteristics due to shared life experiences. In the technology use realm, baby boomers' attitudes and behaviors are assumed to differ from millennials due to their formative years having been markedly different regarding technology access and exposure. While the idea is intuitively compelling, in this paper, we discuss problems with the concept of generations and the proposed mechanisms behind generational differences. We present findings from a systematic literature review investigating generational assumptions and inferences in technology acceptance and use research, revealing a need for a stronger theoretical grounding of generational assumptions and to evaluate other possible causes for differences.

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1 Introduction

Generational differences fascinate academics and practitioners alike, as generational monikers and their attached implications are easy to understand and identify with. Generational cohorts group individuals by birth years and are associated with assumed descriptive characteristics. E.g., millennials are born between 1981 and 1996 (Fry, 2020) and described as “*ambitious, entitled and technologically savvy*” in the workplace (Gabriel et al., 2020). Digital natives and digital immigrants describe a generational dichotomy between the ‘natives’ who grew up with technology and ‘immigrants’ who learned to use it later in life (Prensky, 2001). Digital natives are claimed to be inherently comfortable with technology use, which also purportedly makes them think and behave differently than digital immigrants (Judd, 2018; Mertala et al., 2024). A central premise in most generational research is that core events during an individual’s formative years, such as wars and new innovations, have a profound impact on their subsequent attitudes and behavior.

While popular, generational approaches have been criticized for ascribing every individual within a broad cohort the same values, attitudes, and behavior, for failing to recognize that important life events can impact individuals differently, and for ignoring other than historical influences on human development and the fact that experiences during the entire lifespan have an impact on the individual (Beier et al., 2022). In empirical research, digital natives exhibit diverse attitudes, preferences, use patterns, and access to technologies, they are not uniformly skillful and innovative technology users, and they do not natively speak “the language of computers” (Jones, 2011; Mertala et al., 2024). Over-emphasizing the role of generational membership can be described as causal over-simplification. Purhonen (2016) coins the term *generationalism* for the practice of using generations as the primary explanatory factor for phenomena in the social world. Incorrect categorizations or an over-reliance on generational cohorts can lead to negative implications such as internalized stereotypes (Birkland, 2024), age discrimination (Cox and Coulton, 2015), and poor research designs, for example choosing samples that arbitrarily exclude certain age groups (Goodwin et al., 2023).

Generational research has been extensively scrutinized within workplace research by, e.g., Costanza et al. (2020, 2023) and Rudolph et al. (2018), while a wide and critical debate on the differences between digital natives and digital immigrants can

be found in educational research, as exemplified by Bennett and Maton (2010), Brown and Czerniewicz (2010), and Jones (2011). This dialogue is less prevalent in information systems (IS) research. As many characteristics assigned to various generations describe use of technology or attitudes towards technology, we believe it is important to discuss the possibilities and drawbacks of generational lenses in IS and especially in technology acceptance and use research. In this paper, we report on a systematic literature review with the aims to (1) examine the prevalence of generational research in premier IS outlets, (2) identify problems, fallacies, and good practices within our sample, and (3) provide guidelines for IS researchers interested in applying generational concepts in their research. In the following, we outline the main problems and fallacies that previous research has recognized in generational research and construct a basis for analyzing the prevalence of these problems in our sample.

2 Previous Research

Researchers purport that the empirical evidence for the existence of generational differences is lacking or undistinguishable from alternative explanations (Rudolph et al., 2019; Costanza et al., 2012). Costanza et al. (2020) identify four main categories of issues in generational research: (1) theoretical, (2) methodological, (3) practical, and (4) legal issues. We focus on the first three, as legal issues are beyond the practical scope of our study. Theoretical issues concern whether the conducted research and the drawn inferences are grounded on robust theoretical reasoning in terms of (a) specifying the historical event assumed to produce the differences in a particular birth cohort, (b) specifying what these differences are, and (c) specifying what mechanisms produce these differences (Costanza et al., 2020). Is it reasonable to argue that all members of a particular birth cohort have experienced a historical event in the same way and, thus, can all be assumed to exhibit the differences in the same quantities and qualities? E.g., digital natives are assumed to be more tech-savvy than digital immigrants due to their greater exposure to digital technology during childhood. However, this exposure is not uniform and can vary based on factors such as socioeconomic status in adolescence, leading to differences in technological proficiency among individuals within the same generation. The risk of this fallacy can be considered particularly great when dealing with heterogenous populations or when making comparisons between different countries or cultures (Costanza et al., 2020).

Rudolph et al. (2018) and Rauvola et al. (2019) question the assumption that events stop influencing the development of individuals after adolescence. They suggest that the consequences are dynamic rather than static and might grow, shrink, or even vanish over time. Rauvola et al. (2019) point out that current events are equally likely to influence how people think and behave as core events during adolescence. E.g., most digital immigrants may have been less technologically savvy than most digital natives when entering work life due to lesser exposure to digital technologies in their youth. But the exposure to digital technologies at work may promote their technological skills beyond those of digital natives less exposed to digital technologies at work. In other words, the impact of early life events is exaggerated, and alternative explanations and influences are routinely ignored (Rudolph et al., 2018; Costanza et al., 2023). The risk of falling victim to this fallacy is particularly great when studying older generations because there has been more time for potential development after the historical event.

The methodological issues concern data collection and data analysis. Generational cohorts are commonly operationalized inconsistently, meaning that instead of using the same range of birth years to differentiate between generational cohorts across studies, some studies use arbitrary ranges (Costanza et al., 2012; Rudolph et al., 2018). Ranges may even be entirely driven by the data, for example, to divide the sample into equally sized generational cohorts. Sampling issues are also prevalent, such as whether samples are representative of the intended generational cohorts and sizeable enough for statistical analyses. E.g., Brown and Czerniewicz (2010) criticize the use of student samples to represent a generation, as students are an 'elite' subgroup of the population. Costanza et al. (2020, 2023) criticize the practice of studying generations in isolation. Rauvola et al. (2019) draw attention to the use of subgroup analyses as an error-prone strategy to tease out differences between artificially created groups, especially in the absence of strong theoretical support for the groupings.

A fundamental issue in data analysis is that no statistical analysis method is able to disentangle potential cohort effects (i.e., the differences attributable to the birth year of individuals) from potential age and period effects (i.e., the differences attributable to the age of the individuals or the time period when the data was collected). However, Costanza et al. (2023) suggest that some methods still perform better than others. E.g., instead of using cross-sectional study designs with statistical analysis

methods like t-tests and the analysis of variance (ANOVA), they recommend time-lagged study designs with statistical approaches like cross-temporal meta-analysis (CTMA) and cross-classified hierarchical linear modeling (CCHLM). We summarize the main theoretical and methodological problems in Table 1.

Table 1: Theoretical and methodological problems identified in previous research

Identified problems	Sources
Fuzzy categorization of generations	Costanza et al., 2012; Rudolph et al., 2018; Jones, 2011
Assumption that major events are experienced and impact individuals in the same way	Costanza et al., 2020
Cross-sectional study designs, unsuitable statistical methods	Costanza et al., 2020; Costanza et al., 2023
Assumption that generational differences remain static	Rudolph et al., 2018; Rauvola et al., 2019
Generations studied in isolation	Costanza et al., 2020; Costanza et al., 2023
Student samples representing a generation	Brown and Czerniewicz, 2010
Geographical or cultural context not adapted to	Costanza et al., 2020
Citing unsubstantiated claims (certainty-complacency spiral)	Bennett and Maton, 2010
Only history-related influences considered	Rudolph et al., 2018; Rauvola et al., 2019; Costanza et al., 2023
Lack of acknowledgement and effort to separate age, period, and cohort effects	Costanza et al., 2023
Digital native fallacy; describing young people as inherently tech-savvy	Jones, 2011; Mertala et al., 2024; Bennett and Maton, 2010

Finally, the practical issues concern whether the implications drawn from the conducted research have any practical value (Costanza et al., 2020). In the IS context, one can consider whether results can be used as a basis for managerial actions, e.g., to improve a system. We will next present our study scrutinizing theoretical, methodological, and practical issues in IS technology acceptance and use studies making use of generational concepts.

3 Methodology

Searches were conducted in April 2024 in the Web of Science (WoS) database, limited to research published during the last five years, and only to journals on the AIS Senior Scholars' List of Premier Journals, including those recommended by AIS Special Interest Groups (Association for Information Systems, 2023). Search terms used were "[*generation name**]" AND "*technology acceptance*" OR "[*generation name**]" AND "*technology use*" in all fields. Generations and concepts included in the searches

were: millennials (1 article found), Generation Z (5), Generation Y (0), Generation X (4), boomer (2), generational (10), cohort (129), digital native (6) and digital immigrant (1), amounting to a total of 158 peer-reviewed articles. Subsequently, the websites for the outlets were searched to identify 13 additional articles meeting the selection criteria. After screening the abstracts and removing duplicates, 28 articles from 8 outlets were selected for final analysis. Table 2 shows the distribution of articles over time and outlets. A complete list of selected articles is presented in Appendix A.

Table 2: Overview of selected articles

Outlet	2020	2021	2022	2023	2024	Total
Computers in Human Behavior	2	4	2	3	2	13
European Journal of Information Systems			1	1		2
Information & Management	1					1
Information Systems Frontiers			1			1
Information Technology & People			1	1		2
Journal of Medical Internet Research	2			2	1	5
Organizational Behavior and Human Decision Processes		1				1
Technological Forecasting and Social Change	1		1	1		3
Total	6	5	6	8	3	28

The selected articles were read in full by three researchers over several iterative rounds. During the first round, core research choices were extracted from the articles: (a) generations studied in the research and their indicated start/end years, (b) technolog(ies) examined in the study, (c) geographical/cultural context, (d) underlying theoretical framework, (e) sample description, and (f) methodology. During the second round, the articles were scrutinized for generational assumptions or descriptions underpinning the research and generational inferences drawn from the results. The third round was carried out to discover the presence of any generational research problems or fallacies found in previous research and to identify problems not described in previous studies. Care was taken also to recognize any insightful research choices avoiding the above-described problems and fallacies.

4 Results

Table 3: Generations, countries, and technological contexts of the selected articles

Study	Generations	Country	Context
[1]	Baby boomers, Gen X, Digital natives	Germany	Internet, social media
[2]	Millennials, Gen Z	South Korea	Metaverse platforms
[3]	Digital immigrants, Digital natives	China	Data analytics
[4]	Millennials	N/A	Digital assistants
[5]	Digital immigrants, Digital natives	United States	Online health information seeking
[6]	Millennials	South Africa	Mobile banking
[7]	Baby boomers, Gen X, Millennials	Hong Kong	Gaming
[8]	Gen X, Gen Y, Gen Z	Ghana	E-learning
[9]	Any	N/A	Virtual reality
[10]	Digital natives, other generations	United States	Online learning tool use
[11]	Gen Z, older generations	Switzerland	Health information seeking, digital health literacy
[12]	Digital natives, Digital immigrants	India	Learning management system use
[13]	Gen Z, Millennials, Gen X, Baby boomers	United States	Smartphone use
[14]	Silent generation, Baby boomers	Israel	Digital search engine use
[15]	Junior researchers, tenure-track faculty, tenured faculty	N/A	Pre-registration in open science
[16]	Gen Z	Spain	Mobile learning application use
[17]	Digital natives, Digital immigrants, Silent generation, Baby boomers, Gen X, Millennials	United States	Mobile technology adoption
[18]	Digital natives, Digital immigrants	Europe	Routine and innovative IS use
[19]	Gen Z	Italy	Smartphone addiction, online compulsive buying
[20]	Gen Z	Malaysia, Turkey	AI products
[21]	Gen X, Gen Y	Oman	IoT-enabled healthcare applications
[22]	All	N/A	'Cutting-edge' technologies
[23]	Digital immigrants, Digital natives	United States	Technology interruptions
[24]	Digital natives	France	Smart home technologies
[25]	Baby boomers, Gen Z	United States	Social media
[26]	Baby boomers, Gen X, Millennials	United States	Voice-activated smart home devices
[27]	Digital natives	Myanmar	Consumption patterns, digital flexibility
[28]	Baby boomers, Gen X, Gen Y, Gen Z	Thailand	Mobile health app

As shown in Table 3, the studies have been conducted in a variety of country contexts and with a diverse range of target technologies. Most of the articles study two or more generations, but seven focused on only one (e.g., articles [4] and [6] on millennials). Methodologically, most articles utilize surveys and quantitative

methods, but, e.g., articles [1], [13, study 1], and [23] conducted interviews and qualitative analysis. In turn, articles [9] and [22] are literature reviews. In the following, we discuss theoretical, methodological, and practical issues identified in our sample.

4.1 Theoretical issues

We identified three kinds of theoretical issues in the reviewed articles: (1) missing or ambiguous theoretical reasoning, (2) using generations as a proxy for other theoretical constructs, and (3) conceptual confusion regarding generations and age groups. In the case of missing or ambiguous theoretical reasoning, the reviewed article either lacked all argumentation or provided ambiguous argumentation for how and why the studied generations are assumed to differ, as well as how and why these differences are assumed to impact the phenomenon under investigation. An example of this is article [10], which hypothesizes digital nativity to act as a control variable for academic enjoyment, academic anxiety, satisfaction with learning process, and personal performance but does not present any theoretical argumentation for the proposed effect. Another example is article [16], which evaluates the efficacy and use of a new mobile learning platform among Gen Z, motivated by the statement that this generation “*has unique characteristics that require new teaching strategies*” (p. 2). However, the article does not provide details on what these characteristics are, and how and why they result in the requirement of new teaching strategies.

Many of the reviewed articles use generational cohorts as a proxy for other characteristics without actually measuring those characteristics. For example, some studies assume that younger generations, such as Gen Z, are more innovative than older generations, like baby boomers. While they might provide reasoning for why this difference is expected, they do not test whether the younger participants in their study really are more innovative than the older participants. Instead, they take the assumed generational difference as given and use it as the foundation of their analysis. This approach is problematic because it relies on stereotypical assumptions rather than empirical evidence. If innovation levels vary within generations – meaning that not all young people are more innovative than all older people – then using generations as a proxy for innovation can lead to misleading conclusions. An example of this is article [18], which studies the differences between

digital natives (DNs) and digital immigrants (DIs) and states: *"to communicate with colleagues, DNs use social networks while DIs use traditional communication modes"* (p. 2804) and *"while DI usually resist new technology, DN are more receptive and open to them"* (p. 2806). Although these characterizations may hold true for some digital natives and digital immigrants, they may also vary considerably within the group. Measuring the actual use of communication tools and level of technology resistance is a more reliable approach than assuming it from the fact that they belong to a specific generation.

Some of the reviewed articles did not consistently use generations (individuals born within a specific range of years) and age groups (individuals of a specific age) as two separate concepts but mixed them together, resulting in conceptual ambiguity. An example of this is article [13], which studies the interplay between smartphone use, flow, and well-being, focusing on two age groups: individuals under 24 years and individuals aged 24 years or over. Despite defining these as age groups, the article frequently refers to the younger group as Gen Z. This creates confusion on what is actually being measured: the differences between age groups (which would apply to all individuals of a certain age, regardless of birth cohort) or between generations (which would apply specifically to people born within a particular time range, independent of their current age)? The lack of clarity in distinguishing these concepts weakens the study's theoretical foundation and makes it difficult to interpret the findings correctly.

4.2 Methodological issues

We identified four kinds of methodological issues in the reviewed papers: (1) inappropriate operationalization of generations, (2) inconsistent operationalization of generations, (3) inappropriate statistical analyses, and (4) non-representative or small generational samples. In the first case, the reviewed articles referred to 'generations' that were not really generations, meaning that their operationalization was not based on the range of years when its members were born but on some other characteristic of its members. For example, in article [12], digital natives and digital immigrants are operationalized based on individual computer engagement, measured with a scale by Charlton and Danforth (2007), whereas in article [10], being a digital native is measured with a scale based on Bennett et al. (2008). In turn, article [18] uses an even more complex operationalization of digital natives and digital immigrants based on cluster analysis with age and task experience as the clustering

variables. Finally, in article [15], generations are operationalized based on the academic career stage of individuals. On the positive side, this practice partly addresses the issue of using generations as a proxy for other theoretical constructs because the operationalizations of generations are now based on these other theoretical constructs instead of the birth years of their members. On the negative side, these unusual operationalizations of generations introduce even more ambiguity to generational research. To avoid conceptual confusion, it would be preferable to use, e.g., the terms computer engagement, age, and task experience directly, instead of calling them ‘digital nativity’.

Most of the articles operationalized generations based on birth years, but the range of birth years used for a generation varied between the articles, leading to inconsistent operationalizations. E.g., Gen Z is operationalized as individuals born in 1995 or later in article [19], as individuals born in 1997 and later in article [13], as individuals born between 1995 and 2010 in article [11], as individuals born between 1996 and 2003 in article [8], and as individuals born between the mid-90s and the 2000s in article [16].

In the case of inappropriate statistical analyses, none of the reviewed articles use the time-lagged study designs and advanced statistical analyses like cross-temporal meta-analysis (CTMA) recommended by Costanza et al. (2023) but instead use cross-sectional study designs and simpler analyses like t-tests (e.g., [11] and [14]) and ANOVA (e.g., [17] and [13]). Also regression analyses (e.g., [5], [10], [13], and [14]) and structural equation modelling with multiple group analysis (e.g., [3], [12], and [18]) were frequent. Most of the reviewed articles base their statistical analyses on samples not representative of the population or too small for making reliable statistical inferences. E.g., in articles [20], [24], [16], [19], [13], and [18], the sampled digital natives or members of Gen Z are almost exclusively students, meaning that the sample cannot be representative of the whole population of digital natives or Gen Z. This is particularly true in many developing countries where educational opportunities can be closely tied to socioeconomic status (e.g., article [27] conducted in Myanmar). Calling young samples by a generational moniker may partly stem from a desire to avoid criticism for relying on student samples, i.e., camouflaging a student sample by relabeling it as digital natives or Gen Z. In turn, although articles [17] and [13] study the silent generation and baby boomers, respectively, their samples consist

of only 53 members of the silent generation and 25 baby boomers, which can be considered very small samples for making any kind of statistical inferences.

Most of the articles employed quantitative methods, but article [1] carried out focus group interviews with baby boomers, Gen X, and digital natives. The focus groups were conducted in generation-specific groups instead of mixing generations. This study design means that any topics introduced by respondents in one group can appear unique for that generation if not discussed in any of the other groups, creating the illusion of generational differences. A mixed group design might have revealed that members of different generations, in fact, share thoughts and attitudes.

4.3 Practical issues

We identified two practical issues in the reviewed articles: (1) practically non-significant generational differences and (2) suggesting generational differences when only studying one generation. In the case of (1), the reviewed articles may have found statistically significant generational differences, but the size of these differences is practically non-significant. E.g., in article [17], very few statistically significant and even fewer practically significant differences were found between baby boomers, Gen X, and millennials in terms of their perceptions of innovation attributes and their innovation adoption intentions.

In the case of suggesting generational differences by studying only one generation, the articles included only one generation but either explicitly or implicitly suggested differences between this generation and one or more other generations without any actual evidence for the existence of such differences. An example of this is article [19] that studies Gen Z technology addiction. Based on the high level of smartphone addiction and frequent online compulsive buying found among Gen Z in the article, the authors suggest that this generation is especially plagued by addiction and needs special attention to address these problems. This suggestion may be misleading without finding out how frequent these problems are among other generations.

5 Discussion and conclusions

In our review of IS articles published in premier outlets, we found evidence of similar generational fallacies as presented in previous research from the workplace and educational contexts. The theoretical, methodological, and practical issues identified are important to heed in future research in order to advance our knowledge of age and generations in technology acceptance and use. While technology acceptance and use are mainly a secondary interest in other fields, they are central in IS. Researchers in our field should, thus, be diligent regarding conceptual soundness and clarity in any core concepts describing technology use. We propose that IS researchers:

- a. Discuss any theoretical constructs (e.g., computer engagement and computer experience) directly instead of using generations as a proxy.
- b. Measure any theoretical constructs and characteristics of interest instead of assuming their levels in the studied population (e.g., measure the level of innovativeness in the sample).
- c. Be mindful of the difference between generations (a range of birth years) and age.
- d. Avoid sweeping statements about generations (e.g., “members of Gen X are independent”) and take care to explain the theoretical background, meaning, and relevance of any generational descriptions in relation to the study at hand.

We urge IS researchers to not fall into the certainty-complacency spiral when theorizing about generational differences, referring to the practice of supporting arguments by uncritically citing unsubstantiated claims made in other studies (Bennett & Maton, 2010). This is when researchers cite vague statements, such as “younger generations show a dramatic shift in behavior and attitudes”, but the behavior and attitudes are not described and elaborated further either in the cited or the citing research. This leads to a rise in volume and visibility of generational research without an accompanying rise in actual evidence on the existence and meaning of generations.

Theoretically, it would, in most cases, be advisable to forego generational descriptors altogether and avoid ascribing a wide set of characteristics to a large group of people, as the generational approach ignores the high variety within a group and the

possibility of changes over time. Assuming static generational differences is a lost opportunity for researchers to investigate how technology use evolves over the lifespan. Furthermore, researchers designing their studies on the assumption of generational differences risk limiting the depth and relevance of their findings. E.g., researchers might exclude certain generational groups from their sample altogether (typically older generations) or assume that their findings are not applicable to other generations than the one studied. When groupings are made based on wide generational cohorts, researchers forego the opportunity to test for other, more theoretically sound explanations for the potential differences. Also, researchers rarely test whether the generational assumptions forming their study designs are, in fact, correct.

In our review, we see a high prevalence of studies with student samples that refer to these samples as digital natives or Gen Z and generalize the results to the entire population. We caution against assuming that student samples are representative of the entire generation. Students are typically different regarding many characteristics known to influence technology use, such as computer experience and socio-demographic standing. In a similar vein, many studies take place in geographical and cultural contexts highly dissimilar from the countries where the generational descriptions were created. When using generational descriptors from a different context, care must be taken to ensure their applicability regarding, e.g., core events and levels of technological diffusion. In some studies, generational monikers were used more as a catchphrase than a theoretical construct. In these cases, the generations were mentioned only briefly and mostly in the title and introduction of the article. The study designs did not make use of generational cohorts and generational lenses were not used to interpret the results. This practice is essentially harmless, as researchers then steer clear of most generational fallacies mentioned.

In conclusion, we advise researchers to be critical and ambitious when choosing the core constructs for their studies. Many generational studies are explicitly or between the lines grounded on the digital native discourse. While popular, the myth of digital nativeness has not been theoretically proven. Furthermore, we can better advance our theories and understanding when we study specific constructs of interest rather than blanket descriptors of assumed differences. Finally, through striving for a more nuanced understanding of individuals' technology acceptance and use we can avoid

inadvertently strengthening the all too prevalent age discrimination and stereotyping present in technology use research and practice.

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Appendix A: Articles selected for review

1. Mayer, G., Alvarez, S., Gronewold, N., & Schultz, J. H. (2020). Expressions of individualization on the internet and social media: Multigenerational focus group study. *Journal of Medical Internet Research*, 22(11), e20528.
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