Knowledge Behavior Gap Model: An Application for Technology Acceptance

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Abstract. Organizational change initiatives and societal health campaigns often fail or produce unsustainable outcomes. Intense trainings and knowledge sharing not necessarily lead to expected behavioral results. Is there a gap between what people know and what they do? This paper investigates ways for understanding and closing this gap. It reviews the literature related to innovation diffusion and technology acceptance. Based on that, it develops a Knowledge Behavior Gap model, containing four main constructs: knowledge, acceptance, intention, and behavior. To validate the model, a quantitative survey instrument was designed. Using it, eighty-three valid responses were collected. Partial least squares structural equation modeling method was used to analyze the data and test the model. The results demonstrate a strong and significant path from knowledge to behavior that leads through acceptance and intention. Interestingly, the paths from knowledge to acceptance and from intention to behavior both get even stronger with age. Meaning that for older people knowledge is a more powerful predictor of acceptance and intention is a more seriously influencing behavior. As the main contribution to science and practice, the model provides a more consistent way for measuring and predicting the success of envisioned organizational and societal changes. Thus, researchers are encouraged to advance Knowledge Behavior Gap model, while professionals are invited to apply it for enhancing desired transformations towards hyper-performance.

Keywords: Knowledge · Acceptance · Intention · Behavior · Model · Technology · Design · Persuasive systems · Hyper-performance

1 Introduction

Many novel ideas and initiatives often fail. New technologies emerge, but people are not rushing to start using them. With the continuous rise of novel digital innovations, users are more often than ever involved in permanent decision-making with regards to an acceptance and use of these technologies. While traditional user behavior studies distinguish between early adopters and late followers of innovations [28], an increasing everyday complexity is significantly affecting human decision-making capacity. This can

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be seen with the fluctuating rates of adoption and use of wearables, conversational agents at home, autonomous driving, and artificial intelligence. Even after intense trainings and knowledge sharing there may be achieved dissatisfying levels of behavioral results. Is there an inherent underlying bias that people will always do the required right after they have acquired the relevant knowledge?

In the field of information systems, individual acceptance and use of technology has been a prominent research direction for decades [35]. There are available well-known models and theories, such as Theory of Reasoned Action [2], Theory of Planned Behavior [1], Technology Acceptance Model [8], and Unified Theory of Acceptance and Use of Technology [36]. The use of technology is related with the acceptance, but not often related with the knowledge about a technology.

Conversely, the Innovation Diffusion Theory by Rogers [27] states the knowledge is the first step of adopting or rejecting an innovation. Besides, in practice, there is often an expectation of a direct link between knowledge and usage behavior, i.e., that more information shall lead to the preferred behavior or an increase of the willingness of a person to do the behavior. However, knowledge is not always recognized as a relevant and powerful factor in the context of building user acceptance. This may be one of the key reasons behind lower technology adoption rates in many cases. Thus, we suggest that knowledge is an important instrument [24] that impacts acceptance and later technology related behaviors.

Based on that, we propose a hypothesis that knowledge about a technology is an entry point for the process of deciding about technology use. We argue that there is a direct link between knowledge and behavior, but more prominent relations are from knowledge to acceptance, then to intention using technology, and finally to actual use behaviors. We suggest that there can be a potential knowledge to behavior gap. Finally, we build and test a metamodel with the constructs of knowledge, acceptance, intention, and behavior. We aim at investigating our main research question:

What is the strongest path from knowledge leading to (technology use) behavior?

In this paper, we are addressing the research question in the following fashion. In Sect. 2, we review related literature and provide the relevant theoretical background. In Sect. 3, we describe the emerging hypotheses and build the research model. Section 4 outlines the methodological approach and data collection. In Sect. 5, we present our data analysis. Section 6 contains the study results. In Sect. 7, we propose a discussion of scientific and practical implications. Finally, Sect. 8 ends the paper with the conclusions of this study, limitations, and further research.

2 Theoretical Background of the Main Constructs

Existing scientific literature provides valuable insights from several well-elaborated theories and models in the field of technology acceptance and innovation diffusion. Ajzen and Fishbein [2] were working on one of the first behavioral theories, namely a Theory of Reasoned Action (TRA), that tried explaining the interconnectedness of attitude, behavioral intention, and behavior. A few years later, Ajzen [1] offered an extended view on TRA by adding perceived behavioral control, and thus suggesting a Theory of Planned Behavior (TPB). Nevertheless, TPB keeps the linkage of attitude to intention to behavior unchanged. Only clarifies, it is an attitude towards the behavior.

With the advent of rapid information technology progression, Davis et al. [8] expanded the list of independent variables that can impact the attitude towards using a technology and tailored their Technology Acceptance Model (TAM) specifically applicable to the cases of technology acceptance. Later, TAM was further advanced by Venkatesh et al. [36], suggesting more attitudinal variables determining behavioral intention, as well as introducing moderation effects into their Unified Theory of Acceptance and Use of Technology (UTAUT). Meanwhile, an Innovation Diffusion Theory (IDT) was developed by Rogers [27], suggesting that diffusion is the process by which an innovation is communicated over time among the participants in a social system. This perspective adds the important role that knowledge and its dissemination play into explaining the success of technology acceptance and consequent use behaviors. IDT states that knowledge is a key first stage in the adoptive process of an innovation [34], including novel technology.

According to the relevant literature (Table 1), the technology use behavior has been often studied is relation to a behavioral intention to use it and an attitude towards using it, but rarely in relation to the knowledge about the technology. That provides an opportunity to distill and synthesize theoretical background from the prior literature to develop more advanced research models that can better fit the needs of current times. For example, some of the technologies, which were discussed in earlier literature, are simply outdated (e.g., fax machines). A few decades ago, common knowledge about technologies might have been rare, as gathering technical knowledge was much more difficult than today. In contrast, the current world of digitally connected information society is filled with high-quality training videos, open education resources, and voice interfaces with an instant answer to almost every question referring to the internet [20].

Table 1. Main relevant constructs from behavioral and technology use theories.

Theory	Knowledge	Acceptance	Intention	Behavior
TRA [2]		Attitude	Behavioral intention	Behavior
TPB [1]		Attitude towards the behavior	Intention	Behavior
TAM [8]		Attitude towards using	Behavioral intention to use	Usage behavior
IDT [27]	Knowledge	Persuasion	Decision	Implementation
UTAUT [36]		Expectancy	Behavioral intention	Use behavior

Recent research provides evidence how researchers are carefully experimenting with the alterations and extensions of the listed models (Table 1) to increase their prediction accuracy. For example, Ko et al. [15] conducted a study about the Korean smart-work approach, which is a combinatory set of technological, geographical, and organizational freedom in the work style in South Korean. They found that the original TAM might not be fully suitable for the socio-technical, multidimensional complexity of smart-work environments. By testing six potential variables, they found significant influence of the technology appropriation on the tasked performed and the job satisfaction.

Another recent example is a study in the context of autonomous vehicles, conducted by Lindgren et al. [22]. It proposes a TAM extension for an innovation foresight and predicted acceptance of self-driving cars. An important contribution of this study for our research is the introduction of knowledge construct. They found that knowledge (especially, broader information technology knowledge, plus driver education of autonomous vehicles) plays an important role in the acceptance of self-driving cars.

Building upon this literature review, in the next section we are aiming at developing a research model that leverages the most relevant constructs from previous work on technology acceptance and innovation diffusion.

3 Knowledge Behavior Gap Model

More than a century ago, Tarde [31] was investigating the spread of ideas, concepts, and inventions in a society. He stated that any idea must be shared within a given social community to create a significant effect, which he calls a chain of ideas or chain of imitation, which basically describes the diffusional effect of an idea. Based on that, Rogers [27] constructed IDT and rendered more precisely that diffusion can be seen as a group phenomenon, which nowadays is often referred to as mass acceptance. Further, Rogers [28] explained adoption as the individual process of innovation decision or of accepting a new technology from knowledge to persuasion, decision, implementation, and confirmation.

The initial theoretical model by Rogers holds knowledge as the first variable to explain the personal adoption to an innovation. Other relevant literature provides additional examples of knowledge, especially system-related knowledge, as a variable dealing with pragmatic or instructional information enabling an individual to use a certain tool, e.g., [4, 19, 21]. As knowledge can be either broad or narrow and further conceptual or practical [13], for the purpose of this paper, we understand knowledge as the concrete (narrow) knowledge about a certain technology (practical).

Recent research by Moser and Deichmann [23] and Ochmann et al. [24] shows that knowledge is a highly individually perceived and powerful factor, which can vary between persons and cultures. This view follows the call for further studies by Awa et al. [5], where an integration of different acceptance models has been encouraged and knowledge can be used to reduce perceived risks in subsequent behaviors. Further, studies already revealed the influence of knowledge to the adaptation capability, e.g., [14, 30]. In our work, we treat *knowledge* as the understanding about a certain technology in terms of its functionalities and features, which differs from previous experience with the technology.

Measuring technology acceptance is a common denominator of the related theories and models (Table 1). We argue that acceptance is explained by the attitude of an individual based on the perceived usefulness and ease of use of a technology [36]. Moreover, Davis [9] underlines this with a statement that attitude means to accept or reject information technology. In this paper, we consolidate all the attitudinal aspects of previously listed theories under a unified *acceptance* construct. Further, for our research model we consider a construct of *intention* to use a technology according to Stibe [29], which is in alignment with in all the five previously reviewed theoretical models (Table 1). The same applies for the construct of *behavior*, which we treat as a synonym for use behavior [8, 36], implementation [27] and behavior [1, 2].

Based on the above, for the development of our research model (see Fig. 1), we argue that knowledge about a technology is the first aspect, which directly influences an attitude or acceptance of the technology. However, we also hypothesize that knowledge has a lower direct predictive power on the intention and actual use behavior, as such effects are mediated by an acceptance. Thus, we derive the following three hypotheses:

H1: More knowledge about a technology leads to higher technology acceptance.

H2: More knowledge about a technology leads to an intention to use the technology.

H3: More knowledge about a technology leads to an actual technology use behavior.

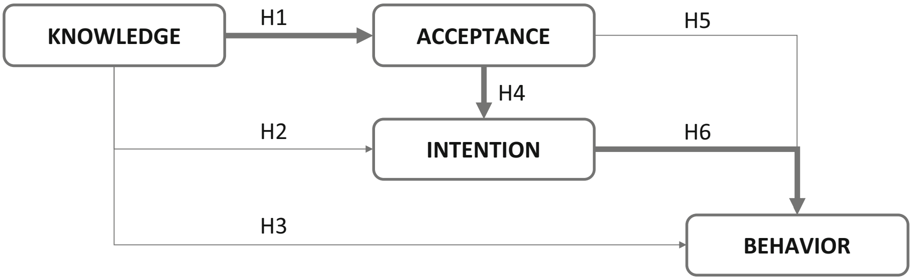

Fig. 1. Knowledge Behavior Gap model with hypotheses.

According to TRA [2], TPB [1], and TAM [8], there is already a scientifically proven correlation between an attitude towards a behavior and behavioral intention. For the research model of our study, we adopt that link as acceptance leads to intention (H4). TPB [8] also suggests that there is a direct impact of perceived behavioral control, another attitudinal construct, on actual behavior. A direct link that bypasses intention. Similarly, also UTAUT [36] suggests that there is another direct effect that bypasses intention. A link between facilitating conditions on actual use behavior. Thus, we also hypothesize that there can be a direct impact of acceptance on behavior (H5). Finally, we include a strongly validated link between intention and behavior (H6), in accordance with the similar model relationships in TRA [2], TPB [1], TAM [8], and UTAUT [36]. To finish developing our research model, we hypothesize that:

H4: Higher technology acceptance leads to higher intention to use the technology.

H5: Higher technology acceptance leads to an actual technology use behavior.

H6: Higher intention to use leads to an increased technology use behavior.

To reflect the main idea of how often there is a gap between people knowing something and whether they are actively applying that knowledge in practice or not, we decided to name it as a Knowledge Behavior Gap model. We hypothesize that in voluntary contexts the strongest path through the model leads from knowledge to acceptance, from acceptance to intention, and from intention to behavior.

4 Research Methodology and Data Collection

For testing and validating the hypotheses of the Knowledge Behavior Gap model, we created a quantitative questionnaire (Table 2) using persuasive systems [12] as a more specific subject for the study. For the questionnaire, we adapted the existing constructs from the reviewed literature.

Table 2. The key constructs and items of the Knowledge Behavior Gap model.

Construct	Items	Description
Knowledge [14, 23, 30]	I know what a persuasive system is I am familiar with what a persuasive system is I don't know what a persuasive system is I am unfamiliar with what a persuasive system is I don't understand what a persuasive system is	Knowledge about a certain technology, which differs from previous experience
Acceptance [35]	I think positively about persuasive systems I have nothing against persuasive systems I am afraid of persuasive systems I feel resistant to persuasive systems I am not accepting persuasive systems in my life	Acceptance can be explained by the attitude towards a technology
Intention [29]	I am sure I will use persuasive systems in the future I consider using persuasive systems in the future I think I will be using persuasive systems in the future I would rather avoid using persuasive systems I don't want to use persuasive systems	Behavioral intention of a person to use a technology

(*continued*)

Table 2. (*continued*)

Construct	Items	Description
Behavior [9]	I am using some persuasive systems currently I have used persuasive systems earlier I frequently use persuasive systems I don't use any persuasive systems at the moment I haven't really used any persuasive systems	Actual technology usage behavior

We collected 83 valid responses in six months. The participants were acquired with the help of social media networks, such as LinkedIn, ResearchGate, and Twitter, as well as direct email invitations and general student acquisition. We were able to generate a spread over four continents within our sample: Europe (Austria, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Latvia, Lithuania, Netherlands, Norway, Portugal, and Sweden), North America (Canada and United States), South America (Brazil), and Asia (Turkey). More descriptive statistics in Table 3.

The main constructs of the Knowledge Behavior Gap model were tested for validity and reliability using SPSS 28 (Statistical Package for the Social Sciences), a statistical software suite developed by IBM for advanced analytics, multivariate analysis, and business intelligence. After that, we implemented a mathematical model in WarpPLS 8.0, a software with graphical user interface for variance-based and factor-based structural equation modeling (SEM) using the partial least squares (PLS). Practically, we analyzed our measurement model by applying PLS-SEM according to Hair et al. [11]. This approach has become popular and further a key approach in multiple research areas, including change management, to validate conceptual models [3].

Table 3. Descriptive statistics of the study sample.

Total number of respondents: 83		Number (#)	Percentage (%)
Gender	Male	50	60.24
	Female	33	39.76
Age	Range	20–74	
	Mean	35.00	
	S.D.	9.90	

WarpPLS software by ScriptWarp Systems as an effective analysis tool for predictive PLS-SEM cases based on existing theories [11]. When it comes to exploratory research, as in this paper, PLS-SEM is a well-accepted method for multivariate statistics [16]. WartPLS software is unique as it enables users to explicitly identify nonlinear functions connecting pairs of latent variables in SEM models and calculate multivariate coefficients of association accordingly [18]. That makes this tool very different from other available software offering only linear functions. It is the first to provide classic PLS algorithms together with factor-based PLS algorithms for SEM [17].

5 Data Analysis

General PLS-SEM analysis results include ten global model fit and quality indices: average path coefficient (APC), average R-squared (ARS), average adjusted R-squared (AARS), average block variance inflation factor (AVIF), average full collinearity VIF (AFVIF), Tenenhaus GoF (GoF), and Simpson's paradox ratio (SPR).

It is recommended that the P values (significance) for the APC, ARS and AARS all be equal to or lower than 0.05, which is the case for our main research model: APC = 0.384, $P < 0.001$; ARS = 0.426, $P < 0.001$; AARS = 0.413, $P < 0.001$. Ideally, both the AVIF and AFVIF should be equal to or lower than 3.3, particularly in models where most of the constructs are measured through two or more indicators. That is true for our model with the values of AVIF = 1.691 and AFVIF = 2.149.

GoF index is a measure of an explanatory power of the model, defined as the square root of the product between the average communality index and the ARS [32]. According to Wetzels et al. [37], there are thresholds for the GoF: small if equal to or greater than 0.1, medium if equal to or greater than 0.25, and large if equal to or greater than 0.36. Thus, our model has a large explanatory power as its GoF = 0.530.

SPR index tells if a model is free from Simpson's paradox instances, which may occur when a path coefficient and a correlation associated with a pair of linked variables have different signs. That may indicate a possible causality problem, suggesting that a hypothesized path is either implausible or reversed. Ideally the SPR should be equal 1, meaning that there are no instances of Simpson's paradox in a model, which is true for our model: SPR = 1.000. Thus, the direction of causality in the model is supported.

To ensure the validity and reliability of the reflective measurement model, we conducted various tests with the most frequent techniques according to Ringle et al. [26]. Thus, we tested the internal consistency reliability with Cronbach's Alpha (CA) and composite reliability (CR), the convergent validity with average extracted variance (AVE) as well as the discriminant validity with the Fornell-Larcker criterion [26]. Validity indicates the degree to which a measurement model can predict what it will be measured. Reliability, in contrast, checks the degree to which the same measured values lead to the same results, which represents the failure rate [6].

We also tested the internal consistency reliability, for which the average correlation of all individual items of the same construct are compared, showing how accurate a group of variables measures a latent variable. The internal consistency reliability is measured by CA and CR [26]. The higher the values of CA and CR the more congruent the items, so the higher the internal reliability. In our model, the CA of all constructs is considerably higher than the suggested threshold value of 0.7, ranging from 0.821 to 0.901 (Table 4). CR should have a value of at least 0.6, which is reflected in our model with values in Table 4 ranging from 0.874 to 0.927, thus our model is internally reliable.

Table 4. Reliability and validity measure (the square roots of AVEs in bold on diagonal).

	Knowledge	Acceptance	Intention	Behavior
CR	0.927	0.874	0.907	0.913
CA	0.901	0.821	0.872	0.882
AVE	0.717	0.584	0.662	0.679
Knowledge	**0.847**	0.381	0.464	0.415
Acceptance	0.381	**0.764**	0.757	0.318
Intention	0.464	0.757	**0.814**	0.554
Behavior	0.415	0.318	0.554	**0.824**

For testing convergent validity, we used AVE, which determines the average percentage of items that explain the dispersion of a latent construct. In the literature, a threshold of 0.5 is mentioned [10], which is the case for all constructs in our model (Table 4), ranging from 0.584 to 0.717. Last, we checked the discriminant validity with the Fornell-Larcker criterion [10]. Therefore, for each construct, the square root of each AVE in the diagonal needs to be compared with the correlation coefficients. Table 4 shows that in our model the AVE is higher in each case so that the discriminant validity is accepted. For more details, Table 5 provides structure loadings and cross-loadings.

6 Results

The structural model with key results is presented in Fig. 2. The β values that are noted next to each arrow demonstrate the strength of relationships between the constructs and the asterisks mark their statistical significance (P value), while the R^2 contributions are presented in brackets. All paths in the model are statistically significant.

The model results evidently demonstrate how the strongest ($\beta = 0.400$–0.689) and the most significant ($P < 0.001$) path emerges from knowledge to acceptance (H1), then to intention (H4), and then to behavior (H6). The other hypotheses are also supported. However, their strengths and significances are considerably lower comparing to the path described above. Knowledge to intention (H2) and to behavior (H3) paths are similar in their key parameters ($\beta = 0.208$, $P = 0.024$–0.023). And acceptance to behavior (H5) path is even comparatively weaker ($\beta = 0.196$, $P = 0.031$).

The total effects and effect sizes are also provided in Fig. 2. Effect sizes (f^2) determine whether the effects indicated by the path coefficients are small (.02), medium (.15), or large (.35). Our study reveals that knowledge has a medium size effect ($f^2 = 0.160$) on acceptance, while acceptance has a large effect size ($f^2 = 0.529$) on intention, and similarly large effect size ($f^2 = 0.337$) intention has on behavior. The coefficient of determination value (R^2) indicates the ability of a model to explain and predict the constructs [26]. The R^2 contributions are marked in the brackets (see Fig. 2). An overall explanatory power of our model is 49.1%, which shows a good predictive accuracy [11]. As the value is around 50%, it indicates that our measurements fit well to our model, and the independent variables well explain the variance of the dependent ones.

Table 5. Structure loadings and cross-loading.

	Knowledge	Acceptance	Intention	Behavior
Knowledge	**0.911**	0.352	0.471	0.357
	0.855	0.364	0.405	0.441
	0.850	0.294	0.412	0.387
	0.800	0.291	0.299	0.309
	0.813	0.304	0.350	0.227
Acceptance	0.219	**0.833**	0.688	0.213
	0.153	**0.742**	0.501	0.084
	0.401	**0.632**	0.388	0.124
	0.284	**0.754**	0.558	0.374
	0.386	**0.843**	0.692	0.338
Intention	0.437	0.521	**0.846**	0.622
	0.335	0.526	**0.815**	0.431
	0.442	0.543	**0.860**	0.631
	0.281	0.739	**0.765**	0.173
	0.370	0.765	**0.780**	0.345
Behavior	0.375	0.260	0.516	**0.875**
	0.379	0.290	0.469	**0.810**
	0.183	0.257	0.423	**0.802**
	0.284	0.219	0.424	**0.822**
	0.450	0.281	0.436	**0.808**

For exploratory research, WarpPLS software offers a unique opportunity to investigate the nonlinear functions of moderation effects on the connecting pairs of latent variables. In PLS-SEM analysis, moderating effects are providing deeper and richer insights into how various factors can possibly influence the strengths of model relationships. Typically, there are three ways. A moderator is increasing, decreasing, or having no significant effect on a relationship in the model.

In our model, we found that the age of an individual plays a positive (increasing with age) moderating role on the effects that knowledge has on acceptance ($\beta = 0.193$, $P = 0.033$) and intention has on behavior ($\beta = 0.261$, $P = 0.006$), depicted with green arrows in Fig. 2. To have a more detailed perspective on the moderating effects, Fig. 3 provides smooth 3D and focused 2D graphs with low-high values.

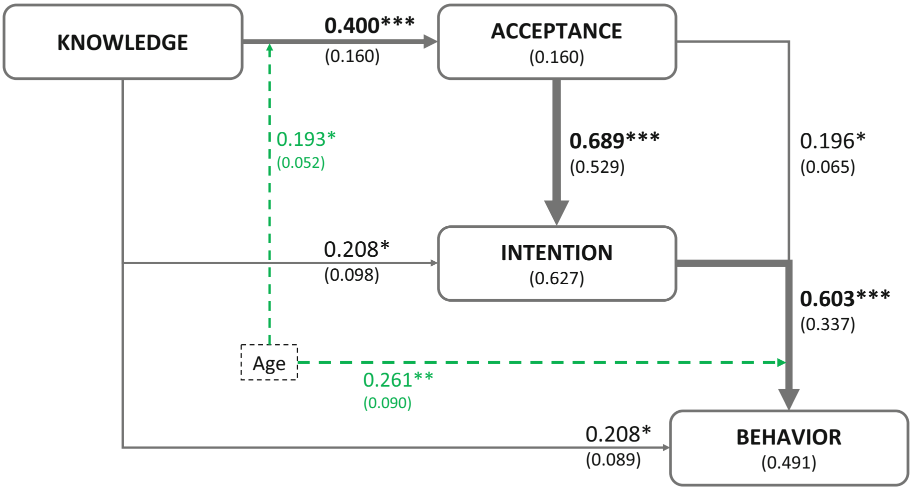

Fig. 2. Knowledge Behavior Gap model with PLS-SEM analysis results.

7 Discussion

The Knowledge Behavior Gap model clearly demonstrates that there is a strong and significant path from knowledge to behavior that leads first through an acceptance of the knowledge, and then through an intention to act upon or use the knowledge in practice, thus leading to an actual behavior.

The knowledge to acceptance relationship (H1) confirms an earlier perspective that has been suggested by Rogers [27, 28] in the Innovation Diffusion Theory, which postulates that the dissemination of knowledge predicts an acceptance of innovations. The further essential model relationships from acceptance to intention (H4) and from intention to behavior (H6) are well aligned with and reconfirming similar model connections from the earlier theories of technology acceptance, such as Theory of Reasoned Action [2], Theory of Planned Behavior [1], Technology Acceptance Model [8], and Unified Theory of Acceptance and Use of Technology [35, 36].

The other paths of Knowledge Behavior model are also significant, but less powerful and smaller effect sizes. It suggests there are people having shortcuts in their process from knowledge to behavior. For example, some people may bypass the acceptance step of the model, because they instantly trust that the new knowledge is relevant and meaningful for their future, so they go straight into planning their intentions (H2). Others can be even more advanced with a quick way for integrating the knowledge into their routines, so rushing directly to do the behavior (H3). Another shortcut in the model leads from acceptance to behavior (H5). Not very strong and significant, but still suggests that there are people that may need to accept the knowledge at first, and once that is achieved, they go straight into action to perform the required behavior.

The Knowledge Behavior Gap model has a potential to profoundly transform an earlier bias that has been commonly maintained in societies and organizations for a long time. An unspoken expectation that once people know how to do something, they

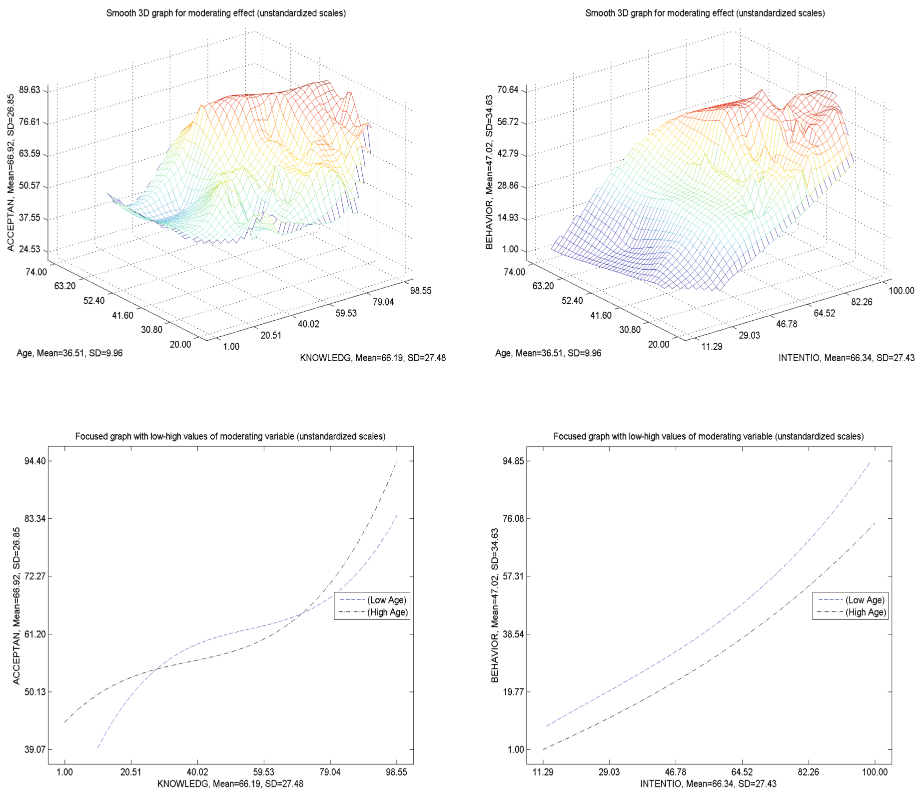

Fig. 3. The moderating effects of age on Knowledge Behavior Gap model relationships.

would go and start doing it, which is often not the case. For example, we can look at the contact tracing apps that have emerged with the recent pandemic. Generally, a large majority of people were aware of these apps. Many did have such an app installed on their smartphones. However, not many had it activated, or they did not use it regularly. If they had been asked about their awareness (knowledge) and importance of slowing down the spread of the virus (acceptance), most likely their responses would have been positive. However, their actions were incongruent with such a mindset.

Interestingly, our study also revealed that two of the main model relationships are shifting their strength and effect size depending on the age of individuals. It suggests that for older people knowledge becomes a stronger predictor for their acceptance, as well as intention becomes a stronger influencer of their actual behavior. Looking at that form the other side, younger people in comparison to older people need less knowledge about a technology to accept it, and lower levels of intention drive them to try using new technologies. This should not support the misperception that older people are less open or more averse for adopting technologies, e.g., [25].

This discovery of our research study demonstrates that older people may need more knowledge about technologies before accepting and using them. A reason might be that older adults consider technology usage more carefully and reflectively comparing to younger individuals [7], because they are not that skilled with technologies than digital natives, for example. These younger people are more likely to trust new technologies because their education and upbringing was generally different in the amounts and access to various technologies. Suggesting that older people need more knowledge about technologies, as well as more intention to use them, comparing to an intuitive trust that digital natives may possess. Thus, the technology adoption for older generations is usually slower than for younger people.

Overall, our findings are in line with and complimentary to the existing models and theories for behavioral and organizational change. Moreover, our work strives to these models with a deeper perspective of the essential steps towards personal technology acceptance. Additionally, we share deeper and richer insights on some of the most interesting moderating effects. That should be helpful for researchers and practitioners to interpret and apply the results with more accuracy and precision.

8 Conclusions

The major contribution of this research study is to propose a Knowledge Behavior Gap model as a response to the long-standing challenges with low efficacy of organizational transformation initiatives and societal wellbeing campaigns. Contrary to an intuitive, but maybe false, perspective that it is enough for people to know for their consecutive behaviors to emerge, our model suggests a more robust and reliable alternative. It describes that the strongest and most efficient path from knowledge to behavior leads through an acceptance first, and then through an intention to do the behavior.

As with many similar studies, our research has a few limitations. First, the amount of eighty-three respondents is not extremely large. Nevertheless, our study employs the PLS-SEM method, which has generated valid results already with even smaller sample sizes [33]. Second, the background of our surveyed sample has limited demographics, so cannot be easily generalized globally. Third, the chosen specific subject of persuasive systems in our questionnaire might have been interpreted differently by the participants. However, we did it on purpose to match the current global trend of more innovative technologies emerging that transform ho we live and work.

For future research, we invite interested scholars to test and validate the Knowledge Behavior model into diverse contexts and with larger sample sizes. Industry professionals and practitioners are welcome to apply and benefit from the model to enhance their desired and long-awaited corporate changes and business transformations. The model can be used to evaluate how people are going to accept and use such digital innovations as, for example, artificial intelligence, augmented reality, metaverse, and more. The Knowledge Behavior Gap model is a fundamental step towards empowering individual and organizational hyper-performance.

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